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Seaweeds and its Applications

Implementing the Cybersecurity

Highlights

A Machine Learning-based Model

Low-Shot Classification Accuracy

Discovering Thoughts, Inventing Future

VOLUME 22 ISSUE 2 VERSION 1.0

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Blind Assistance System using Image Processing

By P. Rama Devi, K. Sahaja, S. Santrupth, M. P. Tony Harsha & K. Balasubramanyam Reddy

Gitam Institute of Technology

Abstract- Eye diseases usually cause blindness and visual impairment. As per the statistics, there are over 285 million visually impaired people living worldwide. They come across many troubles in their daily life, especially while navigating from one place to another on their own. They often depend on others for help to satisfy their day-to-day needs. So, it is quite a challenging task to implement a technological solution to assist them. Several technologies were developed for the assistance of visually impaired people. One such attempt is that we would wish to make an Integrated Machine Learning System that allows the blind victims to identify and classify real-time objects generating voice feedback and distance. Which also produces warnings whether they are very close or far away from the thing.

Keywords: blindness, visual impairment, machine learning, real-time objects.

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BLINDASSISTANCESYSTEMUSINGIMAGEPROCESSING

Blind Assistance System using Image Processing

P. Rama Devi [α], K. Sahaja [σ], S. Santrupth [ρ], M. P. Tony Harsha [Ѡ] & K. Balasubramanyam Reddy [¥]

Abstract- Eye diseases usually cause blindness and visual impairment. As per the statistics, there are over 285 million visually impaired people living worldwide. They come across many troubles in their daily life, especially while navigating from one place to another on their own. They often depend on others for help to satisfy their day-to-day needs. So, it is quite a challenging task to implement a technological solution to assist them. Several technologies were developed for the assistance of visually impaired people. One such attempt is that we would wish to make an Integrated Machine Learning System that allows the blind victims to identify and classify real-time objects generating voice feedback and distance. Which also produces warnings whether they are very close or far away from the thing.

Keywords: blindness, visual impairment, machine learning, real-time objects.

I. Introduction

The fast progress of data and organized technology has advanced from the Internet to applying innovations in life. One of the technologies to consider is objected acknowledgment innovation, later known as object detection. This term denotes a capacity to identify the shape size of diverse objects, and the device's camera catches their position. The practice of detecting real-world object instances in still photos or videos, such as a car, bike, TeleVision, flowers, and humans, is known as object detection. It lets us recognize, localize, and detect many things inside an image, giving us a better overall knowledge of the picture. Image retrieval, security, surveillance, and sophisticated driver assistance systems are all examples of areas where it's applied (ADAS).

Developing accurate Machine Learning Models capable of identifying and localizing multiple objects in a single image has long been a significant challenge in computer vision. However, thanks to recent advances in Deep Learning, developing Object Detection applications is now easier than ever. TensorFlow's Object Detection API is an open-source framework built on top of TensorFlow that makes building, training, and deploying object detection models simple.

Detection of objects can be accomplished in a variety of ways. It is a known fact that the statistical number of visually impaired individuals in the world is nearly 285 million. They face a lot of trouble and constant challenges in Navigation, especially when they are on their own. They need to often depend on someone to get their fundamental daily needs met. So, it is a very challenging task to make a mechanical arrangement for them which is most significant. One such attempt from our project is that we would like to develop an Integrated Machine Learning Framework that permits visually challenged people to distinguish and classify everyday day-to-day objects with voice assistance calculating distance and producing warnings whether the person is close or distant from the thing. The same framework can be used for obstacle detection instruments.

We'll concentrate on Deep Learning Object Detection in this Object Detection project because TensorFlow is based on Deep Learning. Each Object Detection Algorithm works somewhat differently, but they all follow the same basic principles.

Feature Extraction: They use their hands to extract features from input images and utilize these features to identify the image's class. MATLAB, OpenCV, Viola-Jones, and Deep Learning are just a few examples. Tensors are multidimensional arrays that extend the functionality of two-dimensional tables to data with a higher dimension. TensorFlow has numerous properties that make it suitable for Deep Learning. So, without spending any time, let's look at how we can use TensorFlow to develop Object Detection.

COCO dataset comprises around 330K annotated images for Common Objects in Context. Now you must choose a model because you must make a crucial trade-off between speed and accuracy. The main motto for object detection is to find things, drawing rectangular bounding box-like structures around them with distance. Object detection applications are emerging in numerous diverse areas counting, recognizing people, checking agricultural crops, and real-time applications in sports.

Many methods and techniques are introduced to solve the problems of visually impaired people.

This paper gives a compelling presentation on object detection and analyzing the gesture of an object using computer vision and machine learning.

This paper proposed a well-known computer technology part of image processing and computer

Author α: Assistant Professor.
Author σ ρ Ѡ ¥: Students, Department of Computer Science and Engineering, Gitam Institute of Technology, Visakhapatnam, Andhra Pradesh, India.
e-mail: rponnaga@gitam.edu

vision that focuses on detecting objects in computerized pictures or videos. There are various object detection applications with high requirements for face detection, vehicle calculator, and character recognition. Object detection can be used for different applications, including recovery and surveillance. Other essential concepts used in object detection, like using the OpenCV library of python 2.7 progressing in the exactness and effectiveness of object detection, are displayed.

This paper described that everyone wants to live independently, especially the disabled ones. Over the past few decades, technology has helped disabled ones control their livelihood. In this study, an assisting system is propped for the blind using YOLO for the object detection within images and video streams based on deep neural networks to make precise detection, and OpenCV under Python using Raspberry Pi3.The result obtained indicates the proposed approach in providing blind users the capability to travel in unfamiliar indoor and outdoor environments through an object identification model and user-friendly device.

With the rise of more up-to-date and current developments, the world of innovation has prospered at a rapid rate over the last decade. Our lives have become faster due to the use of more recent advances. The rapid advancement of information and arranged innovation has progressed from the internet and mechanization frameworks, which were initially used for regulatory workplaces and mechanical and commercial applications, to the apparatus of those advances all over life. The Internet has also grown in popularity over time. Each family has devised a strategy. Individuals began to seek a more beneficial and superior living environment. They began to consider the use of portable gadgets, apps, and versatile systems in natural checking, machine automation, smart home, and so on. Proficient and precise object recognition is a critical point in advancing computer vision frameworks. The introduction of machine learning and deep learning methods has dramatically increased the precision for object location. The project aims to integrate an Android application for object recognition and localization to achieve high accuracy and real-time performance.

The proposed system aims to create a visual aid image processing system for visually impaired people in which the user accepts speech commands. Its functionality addresses the identification of objects and signs. This will help the visually impaired person manage day-to-day activities and navigate their surroundings.

The paper intends to incorporate cutting-edge object detection techniques in order to achieve high accuracy and real-time performance. In this paper, we use Python in conjunction with a TensorFlow-based approach to solving the problem of object detection from start to finish. The resulting system is quick and precise. A TensorFlow-based application for an Android mobile device is built to detect objects using the device's built-in camera, specifically:

The framework is set up so that an android application (a'suming you're executing it on an Android gadget) will capture real-time outlines and send them to the background of the application, where all the computations take place.

- The video stream is sent and received as an input in the application's background, where it is tested and detected using accurate metrics by the COCO DATASETS object detection model.
- After testing with voice modules, the object's path will be converted into default voice notes, which can be sent to blind victims for assistance.
- In addition to object discovery, we have used an alarm framework to calculate an estimate. If the Blind Person is exceptionally close to the diagram or is far away in a more secure location, it will produce voice-based results in addition to distance units.

The main objective is to identify objects and signboards to help visually impaired persons manage everyday activities. This study will assist blind people by taking speech commands to detect objects using the image processing technique and will provide audio output to the person to track their way around the obstacles. This study will recognize some prominent signboards such as assign for "Washroom" and inform the blind person as soon as the sign is recognized.

II. Review of Literature

1. The current approaches for detecting models were explained in this work, as well as the standard datasets. This work discussed several detectors, such as one-stage and two-stage detectors, which aided in the analysis of various object detection methods and gathered some classic as well as innovative applications. There were also some branches relating to object detection identified. In addition, several development tendencies were identified in order better to follow the set of art algorithms and subsequent processes.
2. A fully convolutional network based on regions was given in this paper. For precise and efficient object detection, R-FCNN is used. As a result, this work can readily use ResNets as fully convolutional image classifier backbones for object detection. For object detection, this research offered a simple but effective R-FCNN architecture. When compared to the quicker R-FCNN, this approach obtains the same accuracy. As a result, it was easier to incorporate state-of-the-art picture classification backbones.
3. This Challenge serves as a reference point for object classification and detection. More than 100 item types and 1 million photos were categorized

and detected in this work. The method for collecting enormous amounts of data is described in this publication. Also, the most efficient algorithm for this data was explained, as well as the successes and failures of other algorithms.

4. The findings of this study revealed that oriented gradient grids outperform the present feature set for human recognition.
5. As object identification technology has advanced, many technologies have been used to autonomous vehicles, robots, and industrial facilities, according to this article. The benefits of these technology, however, are not reaching the visually handicapped, who are in desperate need of them. Using deep learning technologies, this paper suggested an object detection system for the blind. A voice guidance technique is also used to advise visually impaired people about the position of objects. The You Only Look Once (YOLO) technique is used in the object identification deep learning model, and a voice announcement is synthesized using text-to-speech (TTS) to make it easier for the blind to acquire information about items. As a result, it employs an effective object-detection system that aids the blind in locating objects within a given space.

III. Methodology

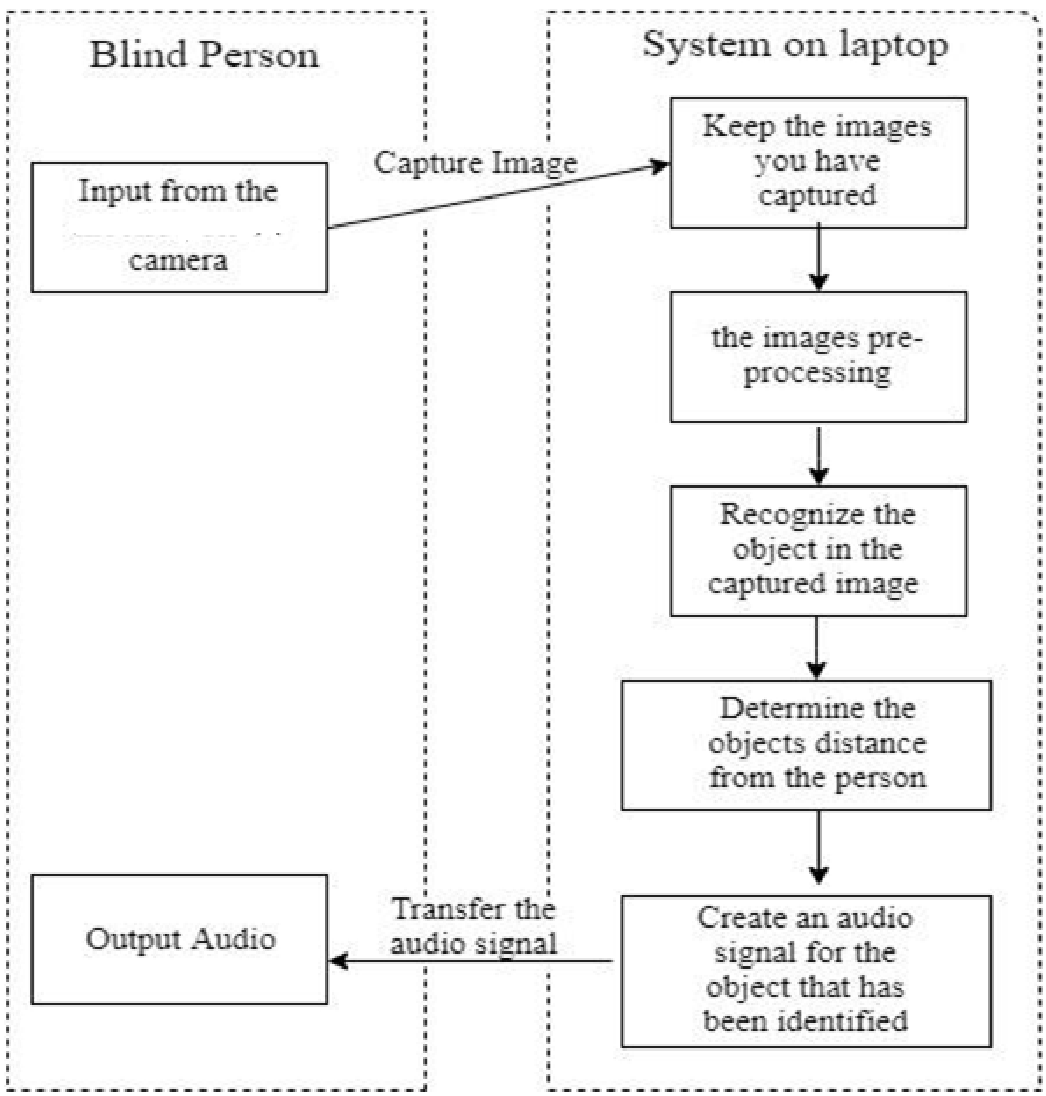

Fig. 1: System Methodology

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IV. Overview of Technologies

TensorFlow API:

Fig. 2: Logo of Tensorflow

We have implemented by using TensorFlow APIs. The advantage we have by using APIs is that it provides us with a set of standard operations. So, we need not write the code for a program from scratch. APIs offer us convenience, and hence they are time savers, beneficial, and efficient. The TensorFlow object detection API is generally a structure built for creating deep learning networks that solve the problem of object detection. There are so many trained models in their framework, and they refer to it as 'Model Zoo.' This includes a collection of the COCO dataset, the KITTI dataset, and the Open Images Dataset.

TensorFlow Object Detection API depends on the libraries mentioned:

- Protobuf 3.0.0
- Python-tk
- Pillow 1.0
- Lxml
- Tf-slim
- Slim
- Jupyter notebook
- Matplotlib
- Tensorflow (1.15.0)
- Cython
- Contextlib2
- Cocoapi

V. Models

Now, a bunch of pre-trained models is with Tensorflow. You can use any one of them. They are pretty good and depending upon your system specifications you can choose one. For a faster accuracy, you can go with SSD DETECTION, and for better accuracy, you can go with MASK RCNN, but most of the system shows smooth performance with SSD Mobile Net DETECTION. So, I'll elaborate on SSD ALGORITHM.

VI. SSD Architecture

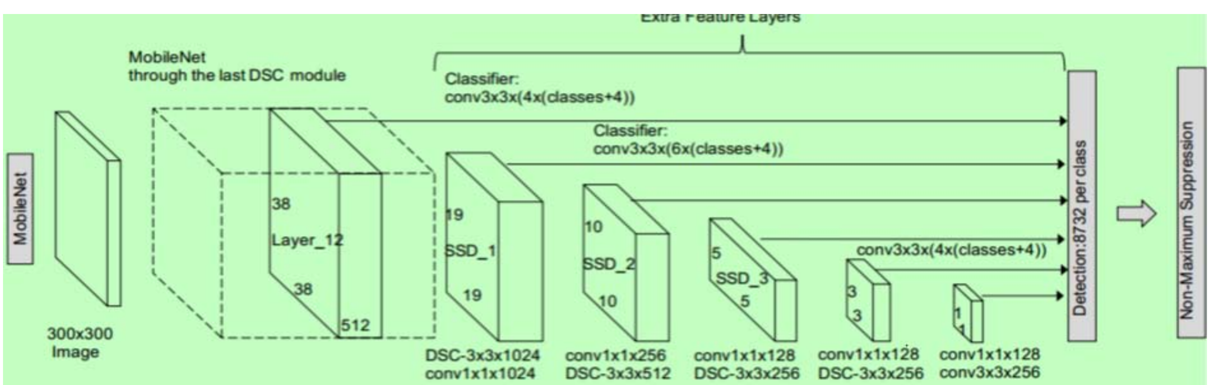

Fig. 3: SSD Architecture

SSD has two components: an SSD head and a backbone model.

The backbone model is basically a trained image classification network as a feature extractor. Like ResNet, this is typically a network trained on ImageNet from which the final fully connected classification layer has been removed.

The SSD head is nothing but one or more convolutional layers added to the backbone, and the outputs are explained as the bounding boxes and classes of objects in the spatial location of the final layer's activations. We are hence left with a deep neural network that is able to extract the meaning of the input image while preserving the spatial structure of the image at a lower resolution.

For an input image, the backbone results in 256 7x7 feature maps in ResNet34. SSD classifies the image using a grid and grid cell responsible for detecting objects in the region of the picture. Detecting objects basically means predicting the class and location of an object within that region.

VII. Anchor Box

Multiple anchor boxes can be assigned to each grid cell in SSD. These designated anchor boxes are predefined, and each one is responsible for size and shape within a grid cell. The matching phase is used by SSD while training so that there's an appropriate match to anchor box with bounding boxes of each ground truth object within an image. The anchor box with the highest degree of overlap with an object is responsible for predicting that object's class and location. Once the network has been trained, this property is used to prepare the web and predict the detected objects and their places. Practically, each anchor box is specified with an aspect ratio and a zoom level. Well, we know that all things are not square. Some are shorter, some are very long, and some are wider by varying degrees. The SSD architecture allows predefined aspect ratios of the anchor boxes to account for this. The different aspect ratios can be specified using the ratios parameter of the anchor boxes associated with each grid cell at each zoom/scale level.

VIII. Zoom Level

The anchor boxes don't need to have the same size as the grid cell. The user might find both smaller or larger objects within a grid cell. To specify how much the anchor boxes need to be scaled up or down concerning each grid cell, the zooms parameter is used.

IX. Mobilenet

This model is based on the ideology of the MobileNet model based on depth-wise separable convolutions, and it forms a factorized Convolutions. This converts basic standard convolutions into depth-wise convolutions. These one × one convolutions are also called pointwise convolutions. For MobileNets to work, these depth-wise convolutions apply a general single filter-based concept to each input channel. These pointwise convolutions use a one × one convolution to merge with the outputs of the depthwise convolutions. As a standard convolution, both filters combine the inputs into a new set of outcomes in one single step. The depth-wise identifiable convolutions split this into two layers — a separate layer for the filtering purpose and the other separate layer for the combining purpose. This factorization methodology has the effect of drastically reducing the computation and that of the model size.

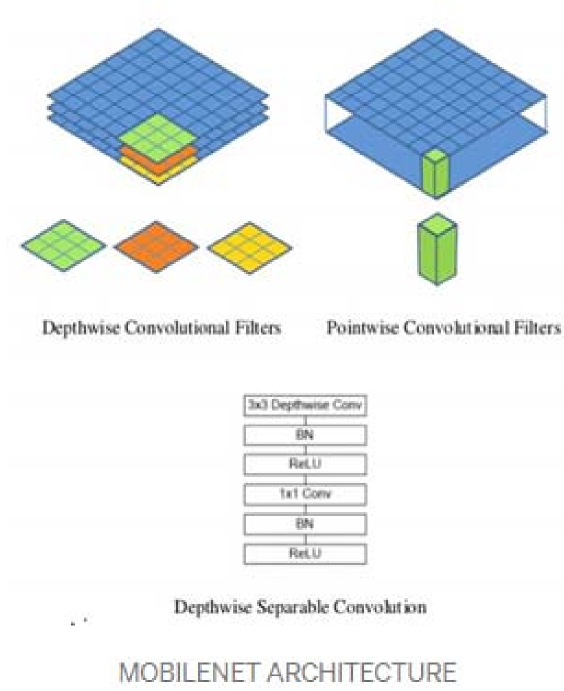

Fig. 4: Mobilenet Architecture

X. Depth Estimation

Depth estimation or extraction feature is nothing but the techniques and algorithms which aim to obtain a representation of the spatial building of a scene. In simpler words, it is used to calculate the distance between two objects. Our prototype is used to assist blind people, which aims to issue warnings to blind people about the hurdles coming on their way. To do this, we need to find how much distance the obstacle and person are located in any real-time situation. After the object is detected, a rectangular box is generated around that object.

Fig. 5: Depth Estimation

If that object occupies most of the frame, then concerning some constraints, the approximate distance of the thing from the particular person is calculated. Following code is used to recognize objects and return the information of the space and location.

```
(boxes, scores, classes, num_detections) = sess.run([boxes,
scores, classes, num_detections],feed_dict={image_tensor:
image_np_expanded})
```

Here, we have established a Tensorflow session comprised of Crucial Features for Detection. So, for further analysis, iteration is done through the boxes. Boxes are an array inside of a collection. So, for iteration, we need to define the following conditions.

```
for i,b in enumerate(boxes[0]):
boxes[0][i][0] – y axis upper start coordinates
boxes[0][i][1] – x axis left start coordinates
boxes[0][i][2] – y axis down start coordinates
boxes[0][i][3] – x axis right start coordinates
```

Index of the box in boxes array is represented by i. Analysis of the box's score is done by index. It is also used to access class. Now the width of the detected object is measured. This is done by asking the width of an object in terms of pixels.

```
apx_distance = round(((1 - (boxes[0][i][3]boxes[0][i][1]))**4),1)
```

We got the center of two by subtracting the same axis start coordinates and dividing them by two. In this way, the center of our detected rectangle is calculated. And at the end, a dot is drawn in the center. The default parameter for drawing boxes is a score of 0.5. if scores[0][i] >= 0.5 (i.e., equal or more than 50 percent) then we assume that the object is detected. if scores[0][i] >= 0.5:

```
                mid_x = (boxes[0][i][1]+boxes[0][i][3])/2
                mid_y = (boxes[0][i][0]+boxes[0][i][2])/2
                apx_distance = round((1 - (boxes[0][i][3] -
boxes[0][i][1]))**4),1)
```

In the above formula, mid_x is the center of the X-axis, and mid_y is the center of the y axis. If the distance apx_distance< 0.5 and if mid_x> 0.3 and mid_x< 0.7 then it can be concluded that the object is too close to the particular person. With this code, the object's relative distance from a particular person can be calculated. After detecting an object, the code is used to determine the relative distance of the object from the person. If the object is too close, then a signal or a warning is issued to the person through the voice generation module.

XI. Voice Generation Module

After the detection of an object, it is of utmost importance to acknowledge the person about the presence of that object on their way. For the voice generation module, PYTTSX3 plays an important role. Pyttsx3 is a conversion library in Python which converts text into speech. This library works well with both Python 2 and 3. To get a reference to a pyttsx. Engine instance, a factory function called pyttsx.init() is invoked by an application. Pyttsx3 is a tool that converts text to speech easily.

This algorithm works whenever an object is being detected, and the approximate distance is being calculated. With the help of the cv2 library and cv2.putText() function, the texts are getting displayed on the screen. To identify the hidden text in an image, we use Python-tesseract for character recognition. OCR detects the text content on images and encodes it in a form that is easily understood by the computer. This text detection is done by scanning and analysis of the picture. Thus, the text embedded in images is recognized and "read" using Python-tesseract. Further, these texts are pointed to a pyttsx. Engine instance, a factory function called pyttsx.init() is invoked by an application. During construction, a yttsx.Driver. DriverProxy object is initialized by an engine that is responsible for loading a speech engine driver from the pyttsx.driver's module. After construction, an entity created by a machine is used by the application to register and unregister event call-backs; produce and stop speech; get and set speech engine properties; and start and stop event loops.

Pytorch is primarily a machine learning library. Pytorch is mainly applied to the audio domain. Pytorch helps in loading the voice file in standard mp3 format. It also regulates the rate of audio dimension. Thus, it is used to manipulate the properties of sound like frequency, wavelength, and waveform. The numerous availabilities of options for audio synthesis can also be verified by looking at the functions of Pytorch.

XII. Results and Discussion

The suggested system is focused on object detection. The technology has been designed to be wearable and portable. The system is attached to the person's chest. The video of the scene is captured by the Raspberry Pi camera, which is then translated into frames by the processor. The auditory output from the system directs the user to the object. Figure 6 depicts the detection of an object (blue cell phone) and a person. A chair is spotted with a person in Figure 7. The system outputs the object's name as well as the object's likelihood as a percentage. As a result, the system will only detect items with a probability larger than the set threshold. Because You Only Look Once (YOLO) is employed to implement the system on the Android platform, the accuracy of object recognition is reduced. It shows the object's name as well as its probability. Through the device's speakers, the programme also informs the user of the class designation and the distance between the object and the camera.

Fig. 6: Image Recognition of person and cell phone

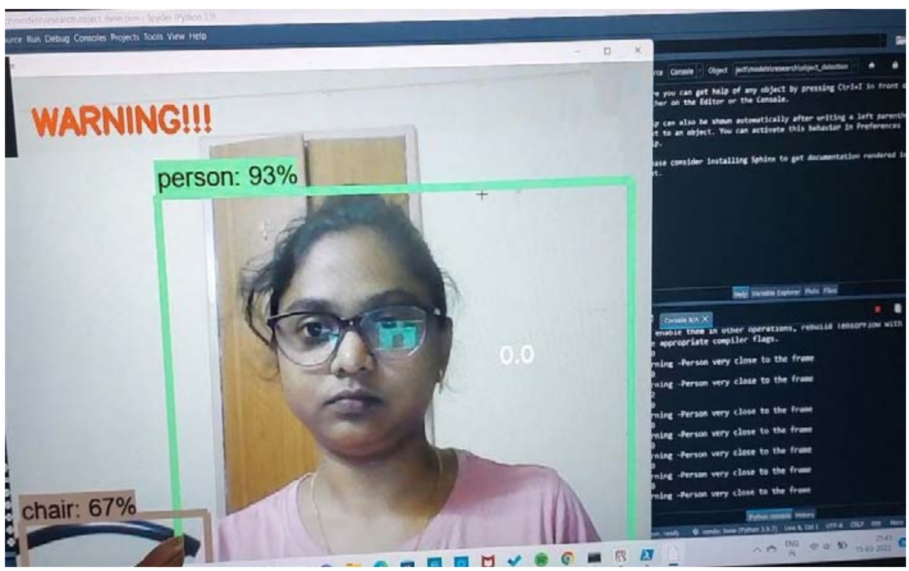

Fig. 7: Image Recognition of person and chair

XIII. Conclusion

Several technologies were developed for the assistance of visually impaired people. One such attempt is that we would wish to make an Integrated Machine Learning System that allows the blind victims to identify and classify real-time objects generating voice feedback and distance. Which also produces warnings whether they are very close or far away from the thing. For visually blind folks, this technology gives voice direction. This technology was created specifically to assist blind individuals. The precision, on the other hand, can be improved. Furthermore, the current system is based on the Android operating system, which may be modified to make it compatible with any convenient device.

Acknowledgments

We also express our thanks to the project reviewers Department of CSE, GITAM University, for their valuable suggestions and guidance for doing our project. We consider it a privilege to express our deepest gratitude to the Head of the Department, Computer Science Engineering for her valuable suggestions and constant motivation that immensely helped us complete this study. Finally, we deem it a great pleasure to thank everyone who helped us directly and indirectly throughout this project.

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Using Unlabeled Data for Increasing Low-Shot Classification Accuracy of Relevant and Open-Set Irrelevant Images

By Spiridon Kasapis, Geng Zhang, Nickolas Vlahopoulos & Jonathon M. Smereka

University of Michigan

Abstract- In search, exploration, and reconnaissance tasks performed with autonomous ground vehicles, an image classification capability is needed for specifically identifying targeted objects (relevant classes) and at the same time recognize when a candidate image does not belong to anyone of the relevant classes (irrelevant images). In this paper, we present an open-set low-shot classifier that uses, during its training, a modest number (less than 40) of labeled images for each relevant class, and unlabeled irrelevant images that are randomly selected at each epoch of the training process. The new classifier is capable of identifying images from the relevant classes, determining when a candidate image is irrelevant, and it can further recognize categories of irrelevant images that were not included in the training (unseen). The proposed low-shot classifier can be attached as a top layer to any pre-trained feature extractor when constructing a Convolutional Neural Network.

Keywords: semi-supervised learning, open-set classification, neural networks, receiver operating characteristic.

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USINGUNLABELEDDATAFORINCREASINGLOWSHOTCLASSIFICATIONACCURACYOFRELEVANTANDOPENSETIRRELEVANTIMAGES

Strictly as per the compliance and regulations of:

Using Unlabeled Data for Increasing Low-Shot Classification Accuracy of Relevant and Open-Set Irrelevant Images

Spiridon Kasapis [α], Geng Zhang [σ], Nickolas Vlahopoulos [ρ] & Jonathon M. Smereka [Ѡ]

Abstract- In search, exploration, and reconnaissance tasks performed with autonomous ground vehicles, an image classification capability is needed for specifically identifying targeted objects (relevant classes) and at the same time recognize when a candidate image does not belong to anyone of the relevant classes (irrelevant images). In this paper, we present an open-set low-shot classifier that uses, during its training, a modest number (less than 40) of labeled images for each relevant class, and unlabeled irrelevant images that are randomly selected at each epoch of the training process. The new classifier is capable of identifying images from the relevant classes, determining when a candidate image is irrelevant, and it can further recognize categories of irrelevant images that were not included in the training (unseen). The proposed low-shot classifier can be attached as a top layer to any pre-trained feature extractor when constructing a Convolutional Neural Network.

Keywords: *semi-supervised learning, open-set classification, neural networks, receiver operating characteristic.*

I. Introduction

Extensive research in the field of machine learning has been progressively improving the performance of object recognition algorithms which achieve impressive results on a variety of multi-class classification tasks [15, 17, 24]. Especially in search, exploration, and reconnaissance applications where object recognition methods have been concentrated on a closed-set setting where all testing samples belong to one of the classes that the classifier has been trained on [29]. The limited finite number of classes which are the target of inspection need to be detected out of the infinite object classes that are encountered in unconstrained environment.

To tackle this challenge, efforts have been made to endow Convolutional Neural Networks (CNNs) the innate human brain capability to identify objects they are trained on while deliberately discarding objects of no interest. Lately, the introduction of open-set classification [20, 31, 30] has introduced an ability to correctly identify images as unknown test objects that do not belong to any known classes, as opposed to falsely classifying them in one of the known classes (i.e., classes that the model has been trained on). More specifically, [28, 10] defines open-set classification as the problem of balancing the known space (specialization) and unknown open space (generalization) of the model. Examples such as out-of distribution detection [18] and realistic classification [26] show the interest in the concept of open-set recognition [4] while showing that CNNs can be trained to reject examples that have not been seen during training or are too hard to classify.

Recently, works on video object discovery [33] go against the closed-set assumption that each image during inference belongs to one of the fixed number of relevant classes. In [33] the terminology of relevant and irrelevant is introduced and is used in this paper since it aligns with the definitions stated in the Abstract. In most real-life applications this closedset assumption is uncommon and ideal, therefore recently proposed methods [4] are subject to an open-set condition where images not seen during training should be classified into irrelevant or unseen classes. Consequentially, in this work we introduce the splitting of testing samples in three categories: (a) relevant; labeled samples used during train-

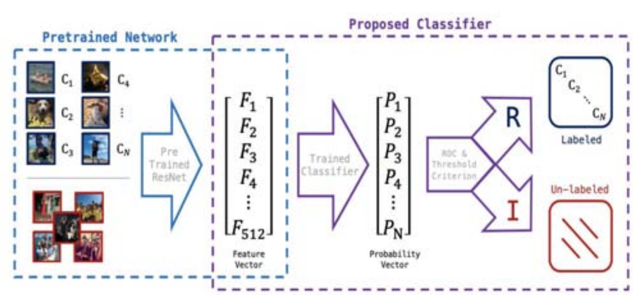

Figure 1: Schematic of the two parts of our network. We feed to the Pretrained Network labeled "Relevant" images and unlabeled "Irrelevant" images. For each image our proposed classifier produces class score vectors that get classified using a threshold criterion and Receiver Operating Characteristic (ROC), with accuracy much greater than already existing techniques, especially for the irrelevant dataset.

Author α ρ: *University of Michigan. e-mails: skasapis@umich.edu, nickvl@umich.edu*
Author σ: Michigan Engineering Services, e-mail: gengz@miengsrv.com
Author Ѡ: US Army DEVCOM GVSC.
e-mail: jonathon.m.smereka.civ@army.mil

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ing, (b) irrelevant; unlabeled samples used during training and (c) irrelevant but also unseen; for categories of images that are not seen during training and should be identified as irrelevant.

Another challenge the visual recognition community faces is the absence of labeled examples. Especially in military applications having large labeled datasets is an unreal expectation as needs and mission tools used for search and reconnaissance evolve. An open-set recognizer will face limitations such as the absence of large amounts of training samples, thus an open-set recognition technique that simultaneously supports the few-shot setting is needed. Therefore, in this paper we propose a low-shot solution to the problem of open-set recognition which considers exclusively the classification layer of a CNN.

Specifically, we present an approach on significantly improving the performance of a simple, time efficient, one-layer classifier on recognising labeled (relevant) images along with non-labeled (irrelevant and unseen as mentioned above) images (Figure 1). The ability to specifically recognize a number (of the order of 50) of relevant classes and also identify when an image does not belong to any of them in a labelinexpensive way is one of the main motivations for low-shot open-set recognition.

Efforts with similar goals have been concentrated on the training of the entire CNN. For example, the PEELER algorithm [25] combines the random selection of a set of novel classes per episode, a loss that maximizes the posterior entropy for examples of those classes, and a new metric learning formulation in order to train the weights of a CNN in such a manner that it can recognize images of a limited amount of classes (≤ 20) that are unseen during training. Dhamija et al. [7] proposes the introduction of two loss functions that are designed to maximize entropy for unknown inputs while increasing separation in deep feature space by modifying magnitudes of known and unknown samples. Although the work of Dhamija et al. introduces the concept of unknown sample recognition like we do, the number of recognizable classes is still very limited compared to the testing done in our method.

Both of the aforementioned algorithms train the entirety of the CNN, unlike the methods proposed by Kozerawski and Turk [23] which can augment any few shot learning method without requiring retraining in order to work in a few-shot multiclass open-set setting. Although not concerned with one-class classification, a similar approach is followed in our work too, where we utilize a pre-trained feature extractor (such as the ones publicly available by PyTorch[1]) and propose an independent open-set low-shot classification method which can augment any existing feature extractor.

To explore the open-set low-shot problem in a holistic, non-specific and easily applicable way, we concentrate only on the training of the classification matrix (matrix used to turn the feature vector to a probability vector in Figure 1), using the pre-trained ResNet feature extractors [15] discussed in Section 2. We reduce the image matrices to feature vectors [8, 1] which are then used in Section 4 to train the classifier with the help of the analytic derivative of our loss function and a unique, partially labeled, target matrix. In Section 5, we use the classification variability statistics and a Receiver Operating Characteristic (ROC) curve as a method to calculate threshold scores for each relevant class. An approach that uses random selections of unlabeled irrelevant images during each epoch of the classifier training is introduced. Testing datasets are used in Section 3 for determining the ability to effectively classify all Relevant, Irrelevant and Unseen datasets. In the last Section we make some closing remarks on our work presented in this paper.

In summary, the contributions of this work are the following:

- We present a novel open-set low-shot (OSLS) classification method which can be added as the top layer to any pre-trained feature extractor in order to create a CNN that can classify images in relevant classes and also determine if an image does not belong to any of the relevant classes.
- The OSLS Classifier yields improved classification performance compared to classifiers that either do not use unlabaled images during training or assume all unlabeled samples to belong in the same class.
- The number of image classes the OSLS is able to classify is greater than the ones used in the open-set classification literature [10, 7, 25].

II. Feature Extractor

Deep Residual Networks have been proven to be a very effective in mapping images to a meaningful feature space, especially when trained from large datasets [32]. In this work we use ResNet18 and ResNet34 [16] to map the sample images to the vector space. Both architectures produce 512-long feature vectors which compared to deeper network feature products lead to a shorter algorithm running time. The different types of ResNets we used, although not very different, will be discussed in Section 3. The weights were trained using the ImageNet1k dataset [6] which involves a large-scale ontology of images. The development of the feature extractor itself is out of the scope of this paper and pre trained feature extractors available by PyTorch are used.

Before providing the training images feature vectors to the OSLS classifier we normalize them using the following equation:

[1] https://pytorch.org/vision/stable/models.html

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$$F_{norm} = \frac{F - F_{min}}{F_{max} - F_{min}} \quad (1)$$

Where F is a 512-long vector feature map and F_{max}, F_{min} are its respective maximum and minimum values in vector form. This type of basic normalization constrains the F values from 0 to 1. We apply the normalization to prevent the Exponential Loss and its Derivative in Equation 9 and Equation 11, respectively, from gaining extremely high values. Additionally, we demonstrate in Section 6 that this type of normalization significantly increases our method's classification accuracy compared to the more popular softmax normalization. It can be argued that the use of softmax normalization yields poor solutions for open-set recognition as it tends to overfit on the training classes.

III. Datasets

The proposed OSLS classification method is used on a variety of training and testing examples, each using different sample arrangements. To explore the capabilities of the proposed method in different settings, two different datasets are being used: the Caltech256 [11] and a custom Mixed dataset.

To explain with more clarity our method and results, we describe the way the Caltech256 dataset is split in two groups. Caltech256 is an open source dataset, it consists of 256 different image classes and has been recently used a lot as a benchmark for a variety of machine learning applications [2, 9].

Similar to our selection of ResNets, we use an open source and broadly used dataset in order to make our example and results as general and less task specific as possible. As we intend to produce work that is going to be used in the future for specific applications, to give a hint on how the method can be geared towards recognition in unique environments the eight infrared classes (Figure 3) which are available from the Military Sensing Information Analysis Center (SENSIAC) Automatic Target Recognition (ATR) database [34] are used in a number of our tests.

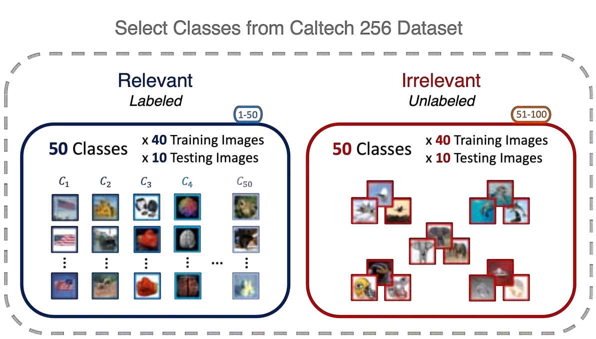

Figure 2: In blue we see the 50 Relevant image classes, and in red the Irrelevant. For training, every class, both labeled and unlabeled contains 40 images, so 2000 labeled and 2000 unlabeled. The evaluation is performed using 10 images for each class, different than the ones used during training.

We train our classifier on both labeled and unlabeled pictures, therefore our main dataset consists of what we call Relevant and Irrelevant pictures. The relevant group is consisted of the first 50 classes of Caltech256 and the irrelevant group contains images from the next 50 classes as shown in Figure 2. To explore the dependency between our classifier visual recognition accuracy and the amount of unlabeled images, we created two more versions of the Caltech256 dataset with an expanded number of Irrelevant images, one has 100 classes of unlabeled images (+50 Irrelevant) and the other has 200 classes of unlabeled images (+150 Irrelevant), both with the same number of pictures per class, 40.

Figure 3: The manually created infrared (IR) dataset using video snapshots from the ATR database consists of eight classes, seven of them are civilian and combat vehicles and the last one is a human class.

Finally, in order to explore the behavior of our method on unique and very different environments from the ones present in the Caltech256 dataset, we created our own infrared (IR) combat vehicle image group by taking snapshots from the publicly available IR videos provided in the Military Sensing Information Analysis Center (SENSIAC) ATR database (examples displayed in Figure 3). The new data product is composed of the same amount of pictures with the one in Figure 2, with the exception that the first 8 relevant image classes are infrared instead of Caltech 256 pictures. Although only

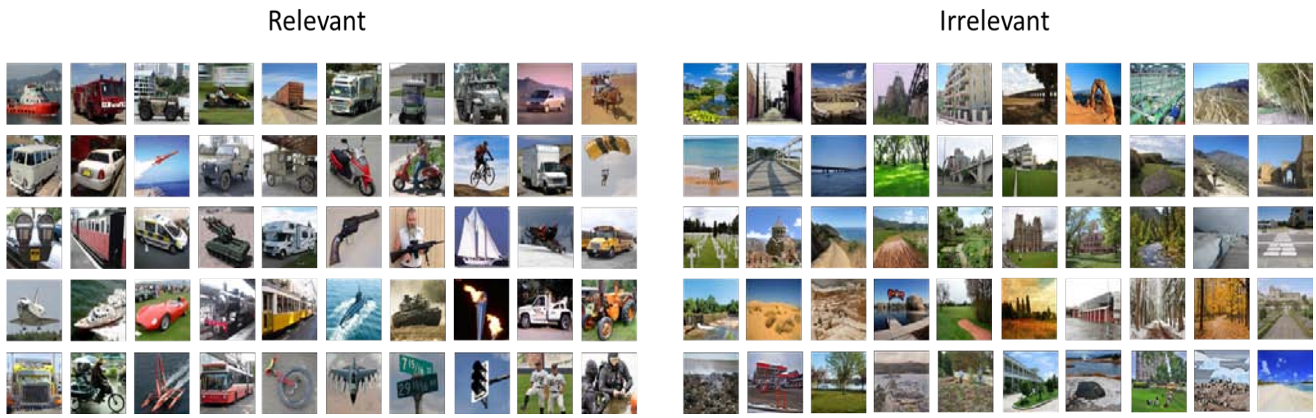

Figure 4: Example images from each one of the 100 classes that comprise the mixed dataset. The 50 relevant images include a variety of different vehicles, humans and weapons while the 50 irrelevant include buildings and outdoor scenery.

8 infrared classes are available in the ATR dataset, the term Infrared Dataset is used to indicate that 8 infrared classes are included within the 50 relevant classes. On the next chapter we discuss how the dataset images described above are treated during the classifier training process.

The second dataset we train and test our classification method on is the Mixed dataset. The relevant group is composed of 50 select classes from the ImageNet [6] dataset and includes pictures of vehicles, aircraft, humans and weapons. This group will serve as the target images that are expected to be recognised. On the other hand, the irrelevant group is composed of 50 classes from the MIT Places [35] dataset which includes a variety of outdoor scenery pictures such as buildings and natural environment. The choice of these two datasets is deliberate as in our application we are trying to recognize objects in a scene and push away scenes that have no relevant objects. Each class on the relevant part of the mixed dataset is comprised of 1,300 images, while each irrelevant class has available 13,000 pictures on average. The imbalance between relevant and irrelevant images is representative of the imbalance in the unlabeled data captured in the field which will contain many more irrelevant objects compared to targeted classes. From every class in both groups, 10 images are reserved for testing the accuracy of the various methods which are compared after the training of the classifier has been completed. When using the Mixed dataset in this work, a part of the irrelevant pictures will be reserved and used as unseen samples (Figure 9), images that have not been seen during training but have to be recognized by the classifier in the same way as the irrelevant.

Examples of the mixed dataset images are presented on Figure 4 while a complete list of the classes in alphabetical order is presented in the Appendix. The way the mixed dataset is utilised for training and testing the low-shot classifier is discussed in Section 5.

IV. Low-Shot Classifier Training

The two integral parts of our classifier training process are the target matrix and the loss function. Our training goal is to tweak the initially randomized weight matrix in such a manner that when multiplying it with a testing feature map, it produces a score matrix whose largest value is the desired class element.

In machine learning, a fully connected layer performs the following calculation:

$$\hat{y} = \sigma(WF + \beta) \tag{2}$$

Where W is weighting matrix of the classifier, F is the feature map matrix, V is the bias vector and f is the activation function. A Singular Value Decomposition (SVD) method solves our matrix equations [21, 19]. The pseudo-inverse method calculation results as:

$$\hat{y} = \sigma WF \tag{3}$$

Here, F is the feature maps,, is the weight matrix which we desire to train, and ˆH is the target, the ideal outcome for the score matrix. Our MATLAB implementation handles the training one class at the time, therefore F is a $N_{img} \times N_{feat}$ matrix and W, is a N_{feat} long vector for each class, where N_{img} is the number of training images in every epoch and N_{feat} = 512 is the length of the feature vectors (constant). With no use of the bias vector, and the reversed order of F and ,to account for the row-column switch, in SVD we calculate the W, matrix one vector (class) at a time therefore essentially solving for the least square solution of:

$$Ax = b \tag{4}$$

When the exact solution does not exist, which means that A is not a full-rank square matrix, we get approximate solutions as:

$$Ax = \hat{b} \tag{5}$$

Therefore the approximation error is:

$$d = \hat{b} - b \tag{6}$$

and in a least-square approach the loss function is:

$$L = ||d|| = \sqrt{\sum_{i=1}^{n} d_i^2} = \sqrt{\sum_{i=1}^{n} (\hat{b_i} - b_i)^2} \tag{7}$$

substituting Equation 6 results:

$$L = \sqrt{\sum_{i=1}^{n} (\sum_{j=1}^{m} A_{ij} x_j - b_i)^2} \tag{8}$$

We introduce an exponential version of the least square solution in order to explore a new, faster converging loss function based on [22]. Our new squared-exponential loss function is:

$$L = \sum_{i=1}^{n} e^{d_i^2} = \sum_{i=1}^{n} e^{(\sum_{j=1}^{m} A_{ij} x_j - b_i)^2} \tag{9}$$

therefore the gradient can be proven analytically to be:

$$\frac{\partial L}{\partial x_j} = \sum_{i=1}^{n} 2e^{d_i^2} d_i A_{ij} \tag{10}$$

and the gradient vector is:

$$\frac{\partial L}{\partial x} = A^T (d. * e^{d^2}) \tag{11}$$

There are two main reasons for choosing this loss function. A squared-exponential function is easy to differentiate analytically and the differentiation is applied to the linear algebra form implemented in the MATLAB code. Note that the dot operator in Equation 11, i.e., $.*$, used with multiplication in MATLAB, creates element wise operations. Compared to other differentiable functions we tested, the square-exponential was the one to converge faster and in a steady way. A problem we encountered, which we solved by normalizing the feature maps as described in Equation 1, is that because of the nature of the function, for numbers greater than 1, the Loss would result in extremely high values.

The gradient matrix in Equation 11 is then multiplied by a learning rate(η) and added to the weight matrix (W), repeating this sequence for every epoch. The steps taken towards training the classifier matrix are therefore all independent from machine learning libraries or functions. Although many different loss functions that get differentiated in a semi-analytic fashion are being used by machine learning libraries, we concentrated our efforts on not using any existing libraries to create a stand-alone method. Therefore the squared-exponential loss function is a good fit.

As in most machine learning applications, the update mechanism used towards convergence is some variation of a normal gradient descent equation. In our specific case we use:

$$W_{k+1} = W_k - \frac{1}{2}\eta \frac{\partial L}{\partial x} \tag{12}$$

Here, in every epoch k, W gets updated by subtracting from it the product of the learning rate [and the gradient matrix. We obtain our learning rate using an algorithm inspired by Iterative Shrinkage-Thresholding Algorithm (ISTA) [3]. We begin with calculating a pseudo-loss which is going to be compared with the actual loss to determine whether the learning rate needs to be decreased or kept as specified on the previous epoch. This iterative method progressively decreases the learning rate as we approach closer to the desired optimal point.

The last, and most unique part about our classification mAs in most machine learning applications, the update mechanism used towards convergence is some variation of a normal gradient descent equation. In our specific case we use:
ethod is our target. As mentioned in the Section 1, the uniqueness of our approach relies on the fact that we make use of unlabeled images during the training of the weight matrix. This is done by extending a typical one-hot encoding [14] matrix to also include class score distributions as targets for the Irrelevant images. Labeled images have arrays of zeros and a unit value on the correct class element as targets.

Irrelevant pictures belong to none of the classes therefore the score for each class should be zero. By experimentation we concluded that the irrelevant target that works best should be a slight negative value, such as -0.2. This intuition matches some of the binary classification work that has been done on Support Vector Machines' (SVM) correlation filters, where 0 and 1 were not as separable as a negative value (-0.1, -1) and 1 [36, 5]. As an example, if a training dataset was consisted of six pictures, half of them labeled and half of them unlabeled, and the labeled ones were members of three different classes, our target matrix would look as follows:

$$\hat{y} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ -0.2 & -0.2 & -0.2 \\ -0.2 & -0.2 & -0.2 \\ -0.2 & -0.2 & -0.2 \end{bmatrix} \tag{13}$$

We train the weight matrix in such a way that during evaluation the irrelevant images class score vector values are spread equally between the classes and acquire values as close to zero as possible. This helps the Irrelevant pictures to score less than the respective class threshold.

Along with using this target oriented training procedure, we also increase our recognition accuracy by calculating our threshold scores using the ROC method as explained in Section 5.

V. Low-Shot Classifier and Roc Threshold Calculation

The multiplication between a feature vector and a weight matrix yields a class score vector. Neural Network classification theory uses the highest score (Top 1, Top 3 or Top 5 have been used too) to group the images into classes. We extend this criterion to make it applicable when unlabeled images are present by introducing a Threshold Score (T_S) value for each class.

The T_S, value serves as a binary discriminating test in order to group pictures in the Relevant and Irrelevant bins. As mentioned above, we don't only need to divide pictures in the two groups, we also want the relevant group pictures to be normally classified in their respective class.

It is important to note that the T_S is calculated during the training of the OSLS. We need the T_S to be pre-calculated before we start evaluating our testing dataset. Once the training has been completed and the $T_S$is known, the classification process runs as follows: a) The testing image runs through the classifier and scores, which denote the likelihood of the image belonging to each class, are calculated. b) The image is assigned to the class with highest score. c) The score of the assigned image is compared to the T_S of the class where it was assigned. If it is higher then it is considered as a member of the class. If lower, it is determined to be an irrelevant image.

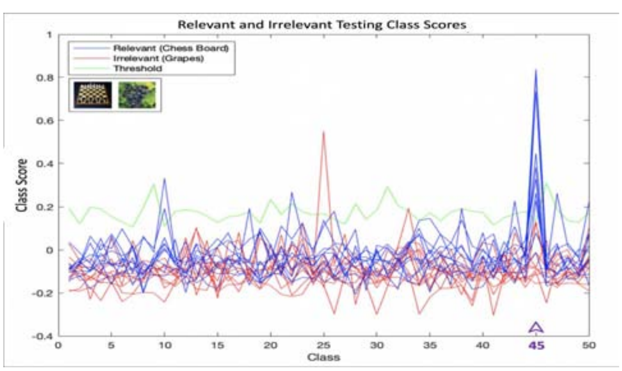

Figure 5: In blue and red we see the 50 different class score values of the 10 different Chess Board and Grapes images respectively. In Green is the ROC threshold calculated for each one of the 50 classes.

Within Figure 5 we present an example where class score values for ten testing images from two classes are plotted. During the training of the classifier matrix we treated the Chess Board pictures as labeled (Relevant), with label 45 attributed to them, and the Grapes pictures as unlabeled (Irrelevant). On the graph we can see that during testing, most of the Chess Board pictures have high class score values on the correct class (45). The correct scores are also above the T_S of this class, therefore they will be classified correctly as members of the chess board class.

On the other hand, the Grapes pictures are treated as Irrelevant during training resulting in lower score values compared to the T_S (green line) of all relevant values. Our target matrix along with our classification method achieves to push the Irrelevant score values lower than the Relevant (red lines below the green line), while keeping the score values for the relevant class above the corresponding T_S (blue lines above green in class 45). Intuitively, we can set the T_S to be the lowest relevant value encountered during the training (Normal Threshold). If a picture is not classified higher than the worst correctly classified training picture, then it should be Irrelevant. As seen in Figure 6, although this discriminatory rule will give us the best possible Relevant accuracy, it will strongly discriminate against Irrelevant pictures.

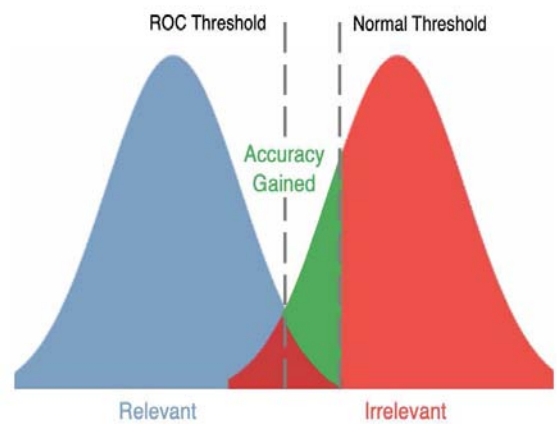

Figure 6: In blue we see the normal distribution of Relevant scores within class X, while in red we see the distribution of the Irrelevant pictures that got classified as class X. Using a normal threshold would classify all Relevant pictures as True Positive, but would hurt the True Negative and total accuracy by a value represented by the green area.

To maximize the combined accuracy we use the ROC curve [27, 13, 12] to chose our threshold values. The same Way we would do with a Normal Threshold, the ROC Threshold is going to be calculated right after training and before testing, using explicitly the training data.

To demonstrate the need of using the ROC T_S, we graph the ROC curves of five, unique compared to each other, classes of pictures that we trained our classifier on. All five classes were part of the labeled dataset (relevant classes). We can see in Figure 7 that every different class of pictures has a 6 different response to the ROC implementation. The different Areas Under the Curves (AUC) represent how well our

ROC method is able to classify the data, but also underlines the need of such an implementation.

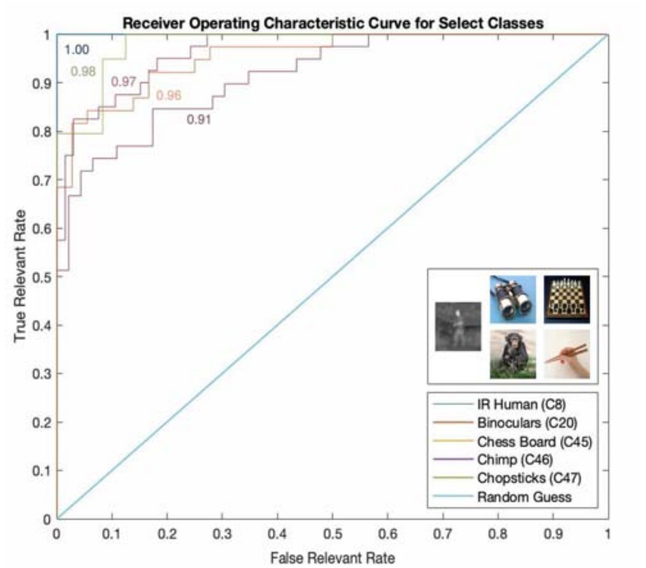

Figure 7: True Relevant Rate is the amount of relevant pictures that our classifier recognized them as such, over the total number of correctly classified pictures. False Relevant is the ratio of pictures that were irrelevant but were predicted as relevant, over the total number of incorrectly classified pictures.

In our analysis we focus on the classification of Relevant pictures, which we assume to be the Positive statistical case, therefore we use the terms True Relevant Rate (TRR) and False Relevant Rate (FRR). TRR and FRR are no different than the True Positive Rate (or Sensitivity) and False Positive Rate (or Fall-Out) respectively, used in statistical analysis.
Therefore we define:

$$TRR = \frac{TP}{TP + FN} \quad \text{and} \quad FRR = \frac{FP}{FP + TN} \tag{14}$$

In Figure 7 it is obvious that the IR Human class is so unique that the classifier does not have any trouble distinguishing it from the rest of the dataset, therefore as seen in the figure above its AUC equals to 1 and the ROC does not have much effect on its cumulative accuracy. Different classes though present different levels of difficulty for our classifier. The Chimp class as seen above, has an AUC of 0.91, which means that the ROC can significantly improve its cumulative accuracy if a T_S is picked wisely.

The Normal Threshold would pick the point on the graph where the False Relevant Rate is minimum for a True Relevant Rate of 1, hence, for the Chimp graph, the ^{1}0.57. 1.00^{o} point. Using our ROC algorithm we can pick any other point on the graph, such as the ^{1}0.20. 0.84^{o} point which is the one further away from the blue line that represents a random guess. By doing this, although we slightly decreased our TRR, we get a great increase in FRR, which results to a significantly higher cumulative accuracy. This accuracy increase is going to be clearly presented and discussed in the next Section.

Tables 1, 2 and 3 demonstrate the usefulness of the ROC method in classifying Relevant images and rejecting an image if it is Irrelevant. In order to highlight the ROC capabilities, we compare our results to the two baseline methods, the "No Irrelevant" and the "+1 Class".

The first baseline result (No Irrelevant), was produced by training the classifier only on labeled images of the relevant classes. This is the case where although we have unlabeled images for the irrelevant classes, we do not use them, expecting the labeled images to have enough meaningful features to accommodate recognizing the irrelevant ones. To evaluate this method, we use our Normal Threshold Score Criterion discussed above where we set the lowest correct relevant training score as the threshold for each class. During testing, if the image's highest class score is larger than the respective threshold then its classified as Relevant, if not as irrelevant.

The second baseline result, which we call "+1 Class", was generated by training the classifier to recognize the relevant classes along with one extra class which encapsulates all irrelevant images. During the training of the classifier, all unlabeled images of the Irrelevant classes were assigned to an extra class. The evaluation is being done by simply comparing the highest scoring index of every image with the correct target.

Table 1 shows how the baseline methods scored for both relevant and irrelevant images compared to the Low-Shot Classifier, with and without applying the ROC optimization for the Top-1 selections.

Table 1: Low-Shot Classifier Compared to Baseline Examples for the Top-1 Selections

	Normal Dataset		Infrared Dataset	
Classifier	R	I	R	I
Low-Shot Classifier	70.8 %	74.8 %	78.2 %	75.4 %
Low-Shot Classifier w/ ROC	64.8 %	87.8 %	71.8 %	89.8 %
+1 Class	49.2 %	91.4 %	56.2 %	92.2 %
No Irrelevant	72.4 %	47.8 %	78.6 %	52.4 %

As "Normal" we describe the dataset consisted of 50 relevant and 50 irrelevant Caltech256 classes and as "Infrared" the dataset where we have substituted 8 of the relevant classes with IR ones. Both datasets are described in Section 3. The Low-Shot Classifier results are obtained by running the algorithm described up until Section 6 and the Low-Shot Classifier with ROC by adding the ROC extension. "R" and "I" are the relevant and irrelevant classification accuracy re-spectively. The

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numbers shown in the tables are the Top-1 percentages of images that got classified correctly during evaluation.

It can be observed that the baseline methods are unable to classify decently both groups of images. The +1 Class method seems to over-train the classifier on recognising the unlabeled images failing to put the labeled ones in the correct classes. This happens most likely due to the unbalanced training data, as the 51st class has as many images as the rest 50 together. On the other hand, by using only labeled images, we train the classifier to specifically recognise the labeled group, failing to filter out the unlabeled images "noise".

In the first row of Table 1, the results of our classifier without the ROC extension show that our loss function combined with our unique target matrix and the threshold score criterion can recognize equally well both labeled and unlabeled images. It is notable that for the relevant group our method loses a small amount of accuracy compared to the label-specific baseline method but does substantially better in identifying irrelevant images.

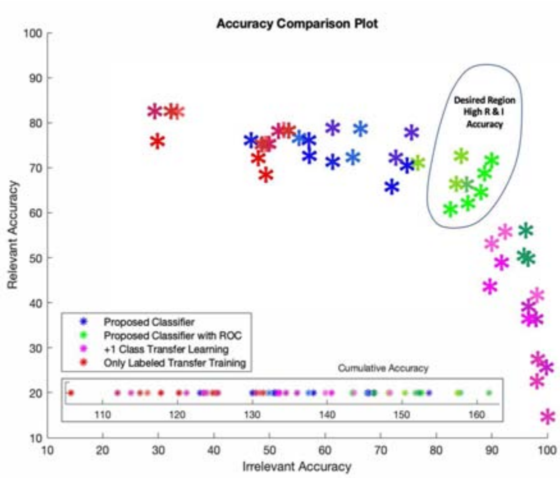

Figure 8: The legend follows the color coding of the four different methods in Table 1. For each of the four methods the graph has four different sub color groups with three data points each. The four different sub groups represent the different datasets discussed in Section 2 and the data points are the three different pre-trained feature extractors used.

The ROC method greatly increases the unlabeled images recognition, to the modest expense of the labeled images. The table shows the importance of using the ROC to greatly increase the cumulative accuracy. Our ROC classifier increases by 12% the cumulative recognition scores compared to the +1 Class method and by 25.4% compared to the label exclusive transfer learning method.

The described results are also depicted in the Accuracy Comparison Graph in Figure 8. For every method discussed we use three different ResNet10 feature extractors (BatchSGM, SGM, L2) in order to show the consistency of our classifier results.

With a few exceptions, no matter the feature extractor or the nature of our dataset (including infrared, including more unlabeled images), our proposed method (green data points) not only provides a higher cumulative accuracy but also eliminates the bias between labeled and unlabeled images by classifying both equally well when compared to the baseline approaches. In the graph we introduced the results of our extended datasets which consists of more unlabeled images.

Table 2 offers a closer look to the comparison of the two extended datasets.

Table 2: Extended Datasets Comparisons

	+ 50 Irrelevant		+ 150 Irrelevant	
Classifier	R	I	R	I
Low-Shot Classifier	79.0 %	66.3 %	76.4 %	56.7 %
Low-Shot Classifier w\ ROC	73.0 %	84.4 %	59.0 %	93.0 %
+1 Class	36.8 %	97.7 %	22.0 %	99.2 %
No Irrelevant	78.6 %	51.9 %	78.6 %	52.9 %

We follow the same notation in Table 2 as used in Table 1, with the only difference being that the "+50" and "+150" Irrelevant datasets are the two expanded datasets noted in Section 3. Although it is clear in both in Table 2 and the plot in Figure 8, that our method still scores better in a cumulative perspective, we can also observe that biases against the relevant (in Low-Shot Classifier with ROC algorithm) or irrelevant (in Low-Shot Classifier algorithm) group begin to occur when increasing the amount of irrelevant images.

We see that for the Low-Shot Classifier the more we increase the irrelevant to relevant ratio the worse we score on the irrelevant part. This might seem counter intuitive as we would expect that the more unlabeled images we see during training, the better we would be able to recognise them. In reality, we introduce many more feature elements on the irrelevant part, which leads to consequently eliminating their uniqueness.

When introducing the proposed ROC approach on the second row (Table 2) we do not observe the introduction of bias because the ROC threshold has been adjusted in such a way that it is non discriminating against any group (OptimalROC). On Table 3 we present the results of our adjusted ROC Classifier being used on the +150 Irrelevant dataset. The same behavior is observed when we test the rest datasets.

The "Optimal ROC" and "No Irrelevant" rows correspond to Table 2 second and fourth data rows. Putting a constraint on how much we are willing to shift the)(to limit the loss in relevant, affects negatively the irrelevant. We desire to find a percentage which during testing gives us a decent cumulative accuracy without big losses on the Relevant part. This could be imagined as turning a knob to tune our ROC

Table 3: ROC Adjustment for the +150 Irrelevant dataset

	R	I	
No Irrelevant	78.6 %	52.9 %	Increase
Optimal ROC	59.0 %	93.0 %	+ 20.5 %
80% Constraint	61.4 %	90.2 %	+ 20.1 %
90% Constraint	68.2 %	82.0 %	+ 18.7 %
92.5% Constraint	72.0 %	77.0 %	+ 17.5 %

implementation. This can be specific in every application, therefore an open ended approach is adopted.

A100% constraint would be the Low-Shot Classifier without ROC, as we set our Threshold Scores to be the lowest correctly classified irrelevant picture in every class. On the table presented, a 90% Constraint means that we ask our ROC algorithm to keep our thresholds to a value that will not hurt our correct relevant guesses more than 10% during the calculation of theT_S. Therefore these constraints are applied when using the training images and they differ from the percentages encountered in the testing (Table 3). As we can see, for the specific case we can compromise with an 18.7% total increase instead of the the 20.5% of the optimal case, in order to get a more equal recognition accuracy.

VI. OSLS Classifier Results

The Low-Shot Classifier is able to recognise images from the relevant classes and also identify irrelevant images from the classes it has seen during training. Ideally, during operation we desire to recognise objects that are not seen at all during training, which is the main objective of openset recognition. To achieve this we extend the capabilities of the Low-Shot Classifier described in Section 3 to recognizing unseen images resulting the OSLS Classifier. The unseen samples are the sub-group of the irrelevant classes that do not get involved in training but it is still expected that the OSLS Classifier recognises them as irrelevant. This is accomplished by randomizing the selection of the irrelevant samples in every training epoch of the OSLS classifier. More specifically, during the training of the Low-Shot Classifier, there are 2 number of classes each of which contain= number of training images for both relevant and irrelevant datasets (only the images for the relevant dataset are labeled). This set of $n \times c$ images is the same in each epoch. The difference in training the Open-Set Low-Shot Classifier seen in Figure 9 is that the irrelevant images are different in each epoch, and selected randomly from the pool of unlabeled irrelevant images while still keeping the total number of irrelevant training images in each epoch the same with the relevant part ($n \times c$). By introducing this imbalance and by not repeating the same irrelevant samples in each epoch, our classifier is able to generalize better on the irrelevant part, yielding better classification accuracy for the irrelevant and unseen testing samples. In all results presented in this paper the testing images are always different than the images used during training.

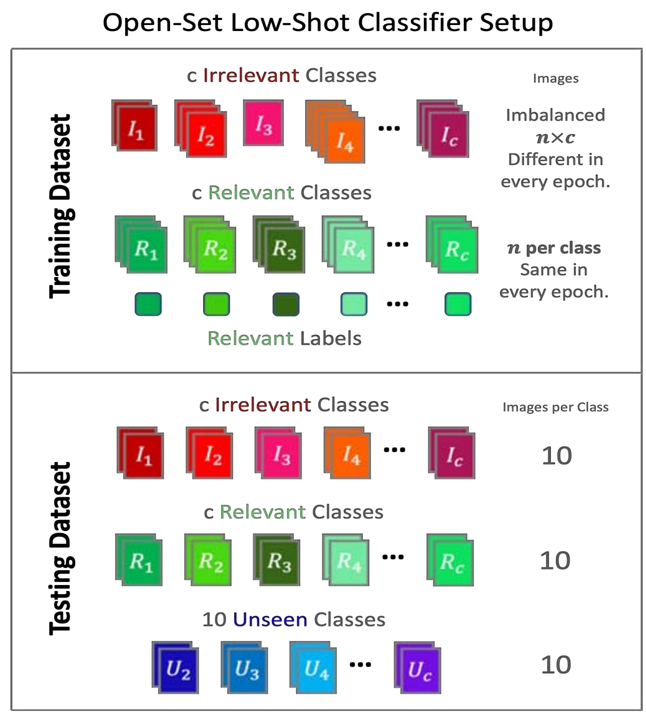

Figure 9: The two differences of the OSLS method compared to the Low-Shot Classifier: We extend our testing dataset to include 10 classes of unseen images (each containing 10 testing samples) while also extending the irrelevant part of the training dataset by introducing randomness and imbalance between epochs and classes respectively. During training, a different selection of irrelevant samples and the same selection of relevant samples is used in every epoch.

A comparison between the traditional (Low-Shot Classifier) and the randomized irrelevant training of the Low-Shot Open-Set Classifier is presented in Figure 10. In this examination, the Low-Shot Classifier training uses the same relevant and irrelevant pictures and classes (40) in every training epoch, whereas the OSLS uses the same set of relevant classes (40) and pictures but samples randomly a different group of irrelevant training images in every epoch. For instance, in the 40 images per class case, the Low-Shot Classifier is trained on the same 40 relevant and irrelevant classes which all include the same 40 pictures for each class. For the OSLS Classifier case, although the 1,600 relevant images (from 40 different classes) are kept the same throughout

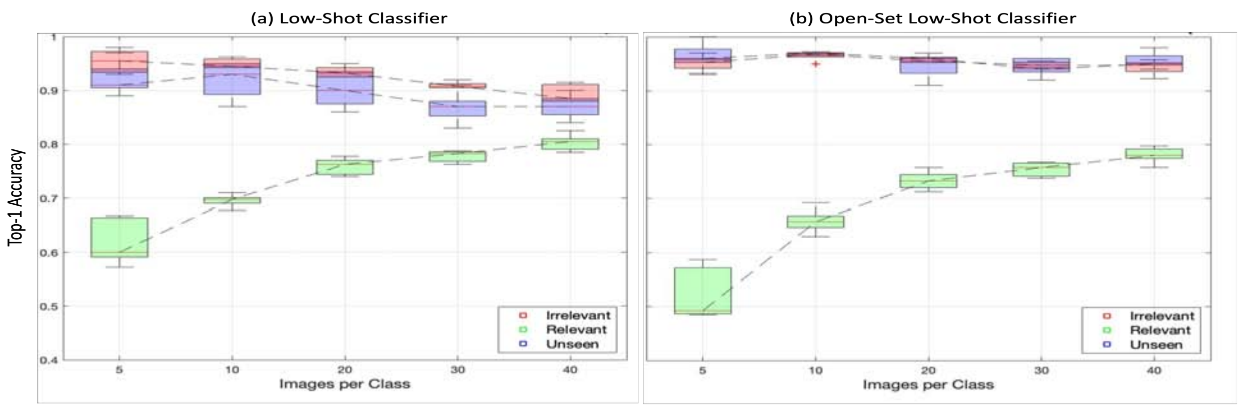

Figure 10: The accuracy box plots for the three different testing groups are presented: in red the Irrelevant, in blue the Unseen and in green the Relevant results. For every Images per Class case, ten different random tests are performed in order to quantify the uncertainty of each case study. The box plot sides represent the median of the lower and upper half of the different results set respectively. The lines extending from the boxes (whiskers) indicate the variability outside the upper and lower quartiles while the red line within the boxes represents the median of the entire spread. Lastly, the red crosses represent the accuracy of the outlier runs and the dashed line connects the median accuracy values of all the different cases.

training, the 1,600 irrelevant images in each epoch are picked randomly from a pool of 20,000 samples (500 samples for each one of the 40 classes), introducing not only randomness but also imbalance between class samples.

Figure 10 demonstrates that by introducing randomness and class imbalance during training, for every Images per Class case there is a slight decrease in the relevant accuracy, but a substantial increase in the testing performance of both irrelevant and unseen. All the results below use the ROC threshold that produces the highest combined relevant and irrelevant score.

All the results presented in the box plots of this text are for an OSLS classifier that is trained on 40 relevant and 40 irrelevant classes, both of which have the amount of relevant images per class specified in the x-axis. Similar works in the open-set literature [10, 7, 25] are using a lower number of classes during training and testing (10 to 95 classes compared to the total number of classes used in this paper ranging between 90 and 250). To show how the OSLS Classifier performs in tests where the same order of classes are used, we vary the number of relevant and irrelevant classes used during training. Although it is of interest to recognize samples of as many classes as possible (a maximum of 40 as presented in Figure 10), by observing Table 4 it is evident that the OSLS Classifier achieves very high Top-1 accuracy scores in situations where the relevant and irrelevant classes we are trying to detect are limited.

We take as an example the case (in bold) where we train the

Table 4: The complete set of results for the OSLS method for a variable number of classes and images per class. Horizontally are presented the results for a variable number of pictures per class (P). Vertically are presented the results for a variable number of classes (C) for each one of the three testing sample categories. For each different example, the mean and standard deviation of 10 different random tests is presented for the Top-1 accuracy.

C \ P	5	10	20	30	40
			Relevant		
5	0.56 ± 0.12	0.61 ± 0.07	0.75 ± 0.09	0.78 ± 0.03	0.83 ± 0.08
10	0.53 ± 0.07	0.66 ± 0.07	0.83 ± 0.03	0.84 ± 0.03	**0.89 ± 0.04**
20	0.53 ± 0.07	0.66 ± 0.02	0.78 ± 0.02	0.83 ± 0.01	0.84 ± 0.05
30	0.51 ± 0.05	0.66 ± 0.03	0.74 ± 0.02	0.77 ± 0.02	0.78 ± 0.01
40	0.51 ± 0.05	0.66 ± 0.02	0.73 ± 0.02	0.75 ± 0.01	0.76 ± 0.02
			Irrelevant		
5	0.95 ± 0.08	0.97 ± 0.03	0.98 ± 0.02	0.98 ± 0.02	0.99 ± 0.01
10	0.93 ± 0.04	0.97 ± 0.04	0.97 ± 0.01	0.98 ± 0.01	**0.98 ± 0.02**
20	0.95 ± 0.04	0.98 ± 0.01	0.97 ± 0.01	0.96 ± 0.01	0.97 ± 0.02
30	0.97 ± 0.02	0.98 ± 0.01	0.97 ± 0.01	0.96 ± 0.01	0.96 ± 0.01
40	0.96 ± 0.02	0.95 ± 0.01	0.95 ± 0.01	0.95 ± 0.01	0.94 ± 0.01
			Unseen		
5	0.93 ± 0.06	0.96 ± 0.02	0.97 ± 0.03	0.98 ± 0.02	0.98 ± 0.01
10	0.95 ± 0.02	0.95 ± 0.04	0.97 ± 0.02	0.96 ± 0.02	**0.96 ± 0.02**
20	0.95 ± 0.05	0.98 ± 0.01	0.97 ± 0.01	0.95 ± 0.03	0.96 ± 0.01
30	0.96 ± 0.02	0.97 ± 0.02	0.97 ± 0.01	0.95 ± 0.02	0.93 ± 0.01
40	0.96 ± 0.02	0.96 ± 0.02	0.95 ± 0.02	0.95 ± 0.02	0.94 ± 0.01

classifier on 10 Relevant and 10 Irrelevant classes each one 10 of which includes 40 training samples- a total of 400 labeled and 400 unlabeled images. By testing using 10 samples per class from 10 relevant, 10 irrelevant and 10 unseen classes the classifier achieves Top-1 accuracy scores of 0.89 ± 0.04, 0.98 ± 0.02 and 0.96 ± 0.02 respectively, with a very low variance between the random runs (f ≤ 0.04).

The OSLS classifier is meant to be used as the final layer of any CNN that is expected to recognise samples that belong to the training classes while identifying as irrelevant images that are not relevant regardless if they originate from seen or unseen during training datasets. In order to demonstrate the versatility of the proposed method we attach the classifier to deeper feature extractors. Throughout the paper the feature extractor used to test any classifier was a pre-trained ResNet18 provided by PyTorch1. In Figure 11 results for a classifier similar to the one in Figure 10 are presented with the only difference being that the feature vectors are produced using the deeper ResNet34. Improvements in accuracy ranging from _ 0.11 to _ 0.02 (for the 5 and 40 Images per Class cases respectively), compared to those of Figure 10b, can be observed for the relevant testing samples while virtually no improvement is observed for the irrelevant and the unseen samples. Similar results are expected if the OSLS Classifier is used as a head for deeper networks which produce feature vectors of higher quality. The improvements can be attributed to the fact that a deeper network has the ability to produce better quality feature representations.

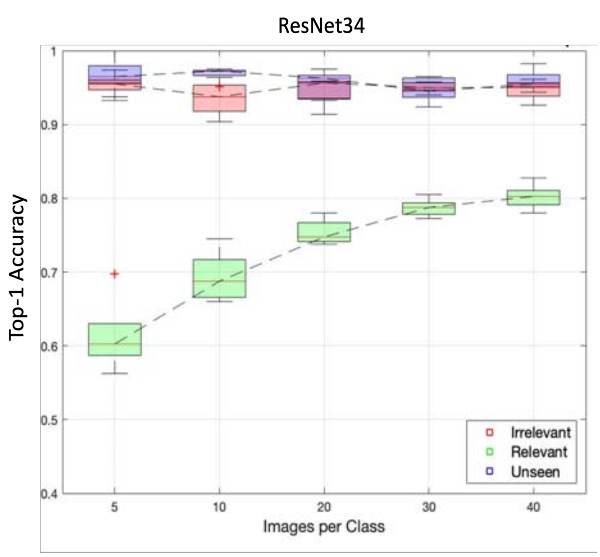

Figure 11: Box plots for the LSOS classifier presented in Figure 10b if the deeper ResNet34 is used to reduce the image samples to feature vectors.

The image feature representations used in this study are obtained raw, before any normalization is applied to them. As mentioned in Section 2, we use Equation 1 to normalized the input feature vectors. Figure 12 exhibits a decrease in accuracy if the features are normalized using the popular Softmax normalization commonly used in classification layers.

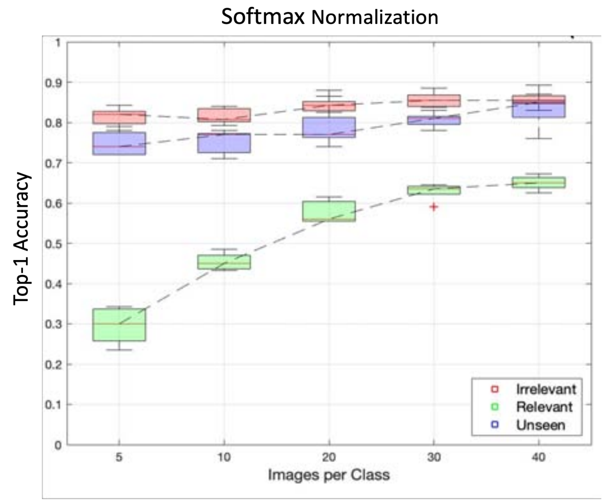

Figure 12: Box plots for the OSLS Classifier presented in Figure 10b if Softmax was used to normalize the training and testing samples.

More specifically, the OSLS results in Figure 10b show an improvement compared to Figure 12 that ranges from ≤ 0.19 to ≥ 0.15 for the relevant, ≤ 0.17 to≥ 0.08 for the irrelevant and ≤ 0.26 to ≥ 0.08 for the unseen testing samples (for the 5 and 40 Images per Class cases respectively).

Finally, in order to demonstrate the value of the OSLS classifier, we compare it to the two baseline examples mentioned in Table 1. The first alternative method (Figure 13a) for classifying relevant samples along with rejecting irrelevant and unseen images is to group all the later in one class during training by assigning the extra class label to them ("+1 Class"). The second method (Figure 13b) the OSLS Classifier is compared to is a normal classification layer which is trained only on relevant images but is expected to recognize irrelevant and unseen images too ("No Irrelevant").

By comparing Figure 10b to Figure 13a, for a low number of samples per class, the "+1 Class" method performs equally well or in cases even better in all three categories compared to OSLS, with relevant accuracy scores ranging from ≥ 0.6 to ≤ 0.7 for the 5, 10 and 20 Images per Class cases while unseen and irrelevant recognition reaching accuracies ≤ 0.96. When enough data samples per class are available though, the OSLS method improves the relevant accuracy by 0.05 and 0.1 for the 30 and 40 images per class cases respectively. The improvement in relevant image classification that the OSLS classification (Figure 10b) achieves is significant compared to the minor (≈0.01) decrease in relevant and unseen accuracy scores.

The benefits of introducing irrelevant images during trainingare evident when comparing the results of Figure 13b (No

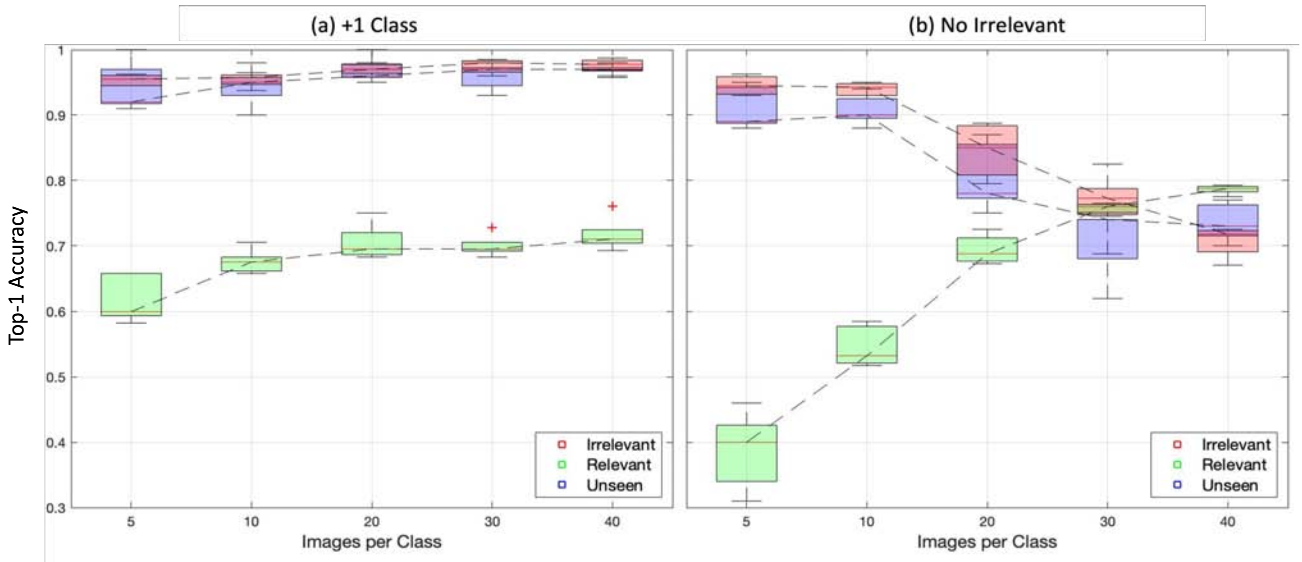

Figure 13: **(a)** The +1 Class method groups all the irrelevant samples in one class during training and expects the irrelevant and unseen testing samples to be classified like they belong to the extra class. **(b)** The No Irrelevant method is a normal classification layer which is trained only on relevant images although expected to recognise irrelevant and unseen images too.

Irrelevant) to the OSLS Classifier results in Figure 10b. If no irrelevant images are available during training and the number of relevant training images per class is small (5 and 10), a normal classification layer tends to over-fit on the later. Due to this over-fitting, the ROC Threshold rejects most of the samples during testing resulting to very high (≥ 0.9) irrelevant and unseen and very low (≤ 0.53) relevant accuracy scores. When there are more training images per class, a significant increase in relevant accuracy can be observed which is followed by a decrease in irrelevant and unseen accuracy. More specifically, assuming similar specifications (normalization, loss function etc.), if a single layer classifier is trained on 40 classes, each one including 40 images, the mean relevant, irrelevant and unseen accuracies during testing are 0.78, 0.72 and 0.73 respectively. If an equal number of unlabeled images are used during training, in the manner specified by the OSLS method, the mean relevant accuracy decreases by 0.02 while the irrelevant and unseen accuracy scores increase by 0.22 and 0.21 respectively. The trade-off between a very small decrease in relevant accuracy and a ten times larger increase in both irrelevant and unseen classification performance is the best demonstration of how the OSLS Classifier can be utilized in real-life applications.

The proposed OSLS Classifier using the ROC Threshold Score criterion not only makes the resulting model more flexible and easy to customize depending on the needs of the datasets, but also makes the method flexible for any application. This is a specifically interesting feature of our work, as we can use the classifier as an extension to any image recognition algorithm which desires to filter out irrelevant and unseen images without the expense of labeling.

VII. Conclusion

In military reconnaissance applications a capability is needed where objects of interest -such as adversary targets- are reliably distinguished from objects of no relevance. Although a modest amount of labeled examples for the targets might be available to use during the training of the classifier, labels for the irrelevant objects might be scarce or even not possible to obtain.

To tackle this problem in this work we present an Open-Set Low-Shot Classifier which is trained using a modest number of labeled images from the relevant classes and unlabeled irrelevant images. A partially labeled target matrix is used for developing an analytically differentiated loss function for training the classifier. At each training epoch a random selection of the irrelevant images used in the training is introduced. During the training an ROC approach is used for determining a threshold score value for each relevant class. The latter is used for providing a balanced performance between classifying relevant samples and identifying irrelevant images.

During testing, this information is used for determining when a candidate image is either relevant, irrelevant or even unseen during training. The OSLS Classifier performs better compared to baseline classifying approaches, is able to handle the classification of many more classes compared to similar open-set approaches in the visual recognition literature and is able to demonstrate sufficient balance with high accuracy in classifying relevant images and identifying irrelevant images.

The code we based our experimentation and results on is available at: https://github.com/skasapis/ROCUnlabeledClassification

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Seaweeds and its Applications: A Review

By Dr. M. S Irfan Ahmed & A. Krishnaveni

Thassim Beevi Abdul Kader College For Women

Abstract- Kelp is one of the main living assets of the sea. Despite their wide applications in food and feed businesses, they have acquired significance as restorative sources due to their high mending, antimicrobial and antioxidative properties. As a rich wellspring of important compound parts, ocean growth is utilized in different businesses like beauty care products, Fuel, water treatment, and so on. Being a plant of remarkable construction and biochemical arrangement, ocean growth could be utilized profoundly for its multi-useful properties as food, energy, medication, and beauty care products. The dispersion, properties, and wide use of kelp are examined exhaustively in this paper.

Keywords: kelp, seaweeds, compound properties, living assets, business.

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SEAWEEDSANDITSAPPLICATIONSAREVIEW

Strictly as per the compliance and regulations of:

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Dr. M. S Irfan Ahmed [α] & A. Krishnaveni [σ]

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Keywords: kelp, seaweeds, compound properties, living assets, business.

I. Introduction

There are many ways that seaweeds are like plants in that they are multicellular, they are photosynthetic, and they are important primary producers. But, the reason why seaweeds aren't plants is that they lack the vascular system of plants. They lack the structures of plants. The plants that everyone knows have to transport liquids internally and seaweeds just don't need to do that. Plants have different sides to their leaves. The top half is different from the bottom half and that's just not true for seaweeds. And the roots, while seaweeds have something that looks like roots, they function very differently. So seaweeds, are their own group. They are their own thing. Seaweeds are called marine algae or macroalgae, and this is to distinguish them from phytoplankton. They are eukaryotic and multicellular and have two important sections. There's the holdfast, which connects the seaweed to the seafloor in that area, and then the thallus, which is the part that is extended up above the holdfast. Now the thallus itself is made out of blades and stipes. So when a person looks at these different structures, the thallus is the main body of the seaweed, and the user has the holdfast, which again sort of look like roots, but behave very differently than roots. The whole purpose or goal of the holdfast is to simply hold the algae in place. It's not bringing anything up from the rocks below, it's not transporting liquid or moisture, things that roots of terrestrial plants would do. So it appears like a root but it doesn't function like a root. The leaf-like structures are called blades. Unlike earth plants, the blades of seaweed are not going to be different from one side that's the top, and to the other side, which is the bottom. These blades on these algae are just going to be swept back and forth by the seawater and so it's not known which side is going to be facing the sun to receive most of the solar input for photosynthesis. The stipe is going to be the body or the connecting portion of that algae. Now, the blades, the stipe, and in fact even the holdfast, all have chloroplasts, and they all have photosynthetic pigment and so really every surface of seaweed is able to photosynthesize. The primary seaweed is either in the haploid or the diploid generation [1-10].

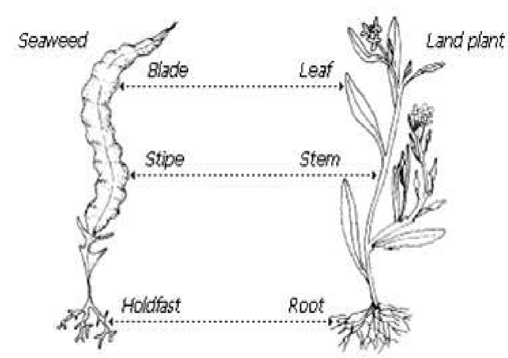

Figure 1: Seaweed structure general biology [9]

Photosynthesis: Sun+CO2+H2O= Nutrients for the seaweed +Oxygen for living persons.

Three Types of Seaweeds:

Overall there are 7000 assessed kelp, 4000 microalgae, and 50 seagrasses (Harbo, 1999). It falls into three general gatherings in view of pigmentation; brown, red, and green kelp [10].

1) Green seaweeds (Chlorophyta)

Typically radiant green in shading there is around 90 types of green kelp in the Pacific Northwest. They have sensitive-looking and clear-cutting edges going from wide to fine hair-like strands which commonly are not all the more than a cell or two thick. Green kelp is normally found in an assortment of territories going from new water streams and springs to saltwater tide pools. They can be open-minded toward a wide scope of water salinities and new water weakening [3].

Author α: Professor & Head, Director, Research-Industry and Institute Relations, Department of Computer Science, Thassim Beevi Abdul Kader College for Women Kilakarai, Ramanathapuram.
e-mail: directortbakc.rir@gmail.com
Author σ: Assistant professor, Department of Computer Science Thassim Beevi Abdul Kader College for Women Kilakarai, Ramanathapuram. e-mail: drakrishnaveni@gmail.com

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Figure 2: Green Seaweed (Ulva) [9]

2) Red seaweeds (Rhodophyta)

Red Seaweeds can be in many tones including, yet not restricted to, dazzling red, pink, purple, dark red, dim, and dark. They are the most bountiful of the three divisions of kelp in our Pacific Northwest waters with around 265 species. They don't need as much light to develop as the green or earthy colored kelp so they are found from the intertidal regions to profundities of 25m. Red kelp is regularly collected for its carrageenan, which is added to food to give it a smooth, velvety surface. Porphyra is collected for nori utilized in Asian foods [4].

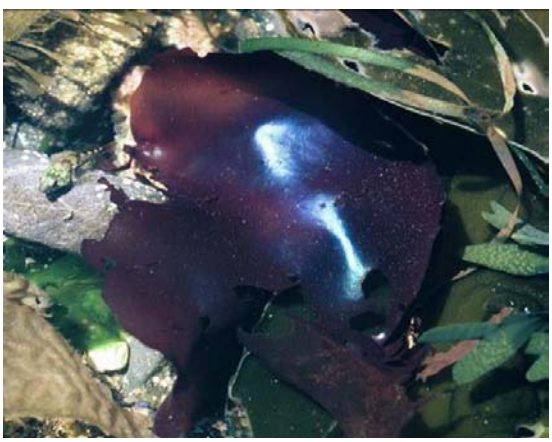

Figure 3: Red Seaweed (Mazzella) [9]

3) Brown seaweeds (Phaeophyta)

Typically gold, brown, olive green, or olive-brown in shading, there are around 140 types of earthy colored ocean growth in the Pacific Northwest. For the most part, they are the biggest and the quickest developing of the kelp however a couple of animal varieties stay little. Bull kelp, Nereocystis, can grow one to two feet each day, developing to be 100 feet in length in a season. Earthy colored kelp is found from the intertidal region to around 15m profound relying upon sun infiltration in the water. Earthy colored kelp (kelps) structure the submerged timberlands of the seas giving an environment to a great many species. They are critical nourishment for some spineless creatures, and kelps have been utilized by local societies for apparatuses and food [5].

Figure 4: Brown seaweed (Nereocystis) [9]

II. Literature Review

Alejandro H. Buschmann et al., [11] reviewed a few parts of kelp creation, for example, a report on the volumes of ocean growth delivered universally by both extractions from normal beds and development. They examine utilizes, creation patterns, and financial examination. Significantly, the authors give a layout to future necessities in the expectation that phycologists all over the planet will adapt to the situation, with the end goal that the possibility to be gotten from ocean growth biomass turns into a reality.

Meenakshisundaram Ganesan et al., [12] momentarily assessed the momentum status of Indian kelp assets and their use, as well as improvements in ocean growth cultivating innovations, the situation with the kelp industry, and ongoing endeavors to change ocean weed cultivating into a social undertaking. It likewise features the difficulties experienced in mainstreaming these assets in order to advance into the marine industry.

Georgia M. Ward et al., [13] surveyed sicknesses that have been accounted for in the logical writing for types of red and earthy colored kelp. The authors have zeroed in on the significant ocean growth crops filled in Asia, where a lot of this creation is trotted. They likewise give data on sickness the executives and biosecurity and a few perceptions on future bearings.

With future increments expected in the force, span, and frequencies of MHWs, Straub SC et al., [14] hope to see more substitutions of enormous seemingly perpetual living space framing kelp with more modest transient ocean growth, lessening the environment structure and successful administrations ocean growth overwhelmed reefs can give.

Kelp is a sustainable marine asset and stands out in the field of scientific classification in India when contrasted with their earthly partners, basically because of the absence of attention to their financial potential. In the current correspondence, Vaibhav A. Mantri wt al., [15] expected to address the situation with kelp biodiversity in India alongside the holes, difficulties, and open doors.

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J. L. Banach et al., [16] study planned to survey the accessible information on the presence of food handling dangers in kelp, including factors impacting their presence, and to focus on the perils that might represent a gamble to human wellbeing.

Through creating quality descriptors for both steamed and dried results of the objective species, Annelise S. Chapman et al., [17] concentrate on establishing the framework for future deliberate tactile examinations. Primer tests uncovered a solid effect of animal groups on tangible insight, with P. palmata having a tactile profile unmistakable from the kelp species.

Nicholas Paul et al., [18] described, "Information is realizing that kelp contains fiber, minerals, protein, and omega-3 oils. Astuteness is realizing kelp are not high in these"? Presumably we can all imagine many models where: "kelp shrewdness" (ethno-phycology) is a higher priority than information; culture development rates and biomass productivities come into view.

Yogesh Kumar et al., [19] presented features of the nourishing and bioactive mixtures happening in various classes of ocean growth while zeroing in on their helpful exercises including but not restricted to platelet conglomeration, antiviral, antitumor, mitigating, and anticancer properties. Their survey likewise investigates the current and possible use of ocean growth as a wellspring of regular cancer prevention agents in food items.

The motivation behind Sami F.J et al., 's [20] study was to decide the bioactivity profile of ocean growth remove Eucheuma cottoni, Sargassum polycystum, and Caulerpa racemosa with the goal that it very well may be created as a restorative unrefined substance. The three sorts of kelp were removed by maceration and bioactivity testing was completed as a cancer prevention agent utilizing the ABTS revolutionary decrease strategy and bioactivity testing as UV-security with the boundaries of the rate transmission of erythema, pigmentation, and Sun Protective Factor (SPF).

Abdul Bakrudeen Ali Ahmed et al., [21] in the long run, developing kelp was a high worth and futile work. Then, at that point, after the states discovered that this thought is a cash making, low-worth, and high-volume item, they begin to put resources into this industry, and imports and products were a lucrative issue. While the ascent of fish utilization on the planet, the development of fish turned into a significant piece of each industry. Fish cultivating and fish creation rely upon freshwater or lake refinement. Kelp helps these societies and increment the yield and quality by creating sustenance in their current circumstance.

Berna Kılınc et al., [22] clarified today China, Japan, and the Republic of Korea are the biggest buyers of kelp as food. Nonetheless, as nationals from these nations have moved to different regions of the planet, the interest in ocean growth for food has followed them, as, for instance, in certain pieces of the United States of America and South America. Expanding requests in the course of the most recent fifty years exceeded the capacity to supply necessities from normal (wild) stocks. Investigation into the existing patterns of these kelp has prompted the advancement of development enterprises that presently produce in excess of 90% of the market's interest.

Cristina Garcia Sartal et al., [23] listed the utilization of alginate in the food business depends on its capacity to expand the thickness of watery arrangements and to frame gels that don't dissolve when warmed. Alginate is utilized as a stabilizer in frozen yogurt and other dairy items, in the brew to create foam, and in sodas. It is utilized as a thickener in beverages and cleansers, as an explaining specialist in wines and juice, and to expand the consistency of organic product juices and mustard (Gonzalez et al., 1998).

Pranav Nakhate et al., [24] expressed ocean growth's ability and likely usefulness to help the bio-based economy are efficiently talked about. The conceivable bioprocessing plant draws near, alongside its natural and financial parts of supportability, which are additionally managed. At last, the formative interaction, side-effect advancement, monetary help, and social acknowledgment approach are summed up, which is fundamental while considering kelp-based items' possibility.

Eduarda M. Cabral et al., [25] expect to give an outline of the overall strategies and novel mixtures with antimicrobial properties as of late disconnected and portrayed from macroalgae, accentuating the sub-atomic pathways of their antimicrobial systems of activity. The current logical proof of the utilization of macroalgae or macroalgal concentrates to expand the timeframe of realistic usability of food varieties and forestall the advancement of foodborne microorganisms in genuine food items and their impact on the tangible properties of different food varieties (i.e., meat, dairy, refreshments, fish, and pastry shop items) will likewise be examined, along with the fundamental difficulties and future patterns of the utilization of marine normal items as antimicrobials.

Adriana Leandro et al., [26] focal point of their review is in the presentation of kelp as a likely other option and as a protected food source. Here portrayed are the health benefit and concerns connecting with ocean growth utilization, and furthermore how kelp inferred compounds are now financially investigated and accessible in the food business, and the use limitations to shield them as protected food added substances for human utilization.

Simone E. M. Olsthoorn et al., [27] deliberate survey sums up data on the effect of earthy colored kelp or parts on aggravation, and irritation-related

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pathologies, for example, sensitivities, diabetes mellitus, and heftiness. They center on oral supplementation hence meaning the utilization of earthy colored ocean growth as food added substances.

Joao Cotas et al., [28] concentrate on features of the three polymers, alongside their known limits, at which they can have positive as well as bad wellbeing impacts. Such information is critical to perceiving the worldview administering their effective sending and related valuable applications in people.

Maria Eggertsen et al., [29] give a synopsis of the flow of logical information on potential immediate and roundabout negative ecological impacts connected to eucheumatoid ocean growth cultivating, for example, modifications of benthic macrophyte natural surroundings and loss of local biodiversity. Moreover, we feature information holes that are of significance to address sooner rather than later, e.g., enormous scope environment impacts and ranches as likely vectors of microorganisms. We additionally give various possible administration suggestions to be executed for the proceeded with the improvement of the earth's reasonable ocean growth by cultivating rehearses in the WIO area.

A biorefinery approach Gabriela S. Matos et al., [30] shows an important thought of tackling financial and natural disadvantages, empowering fewer deposits creation near the much suggested zero-squander framework. The point of this work is to report on the recently evolved techniques for ocean growth extractions and the likely utilization of the parts extricated.

Kelp's recorded use in everyday food diet, partnered to explore discoveries, showed that macroalgae are a wellspring of supplements and bioactive mixtures with nutraceutical properties. The principle objective of Diana Pacheco et al., [31] review is to assess the records of NIS ocean growth in the Iberian Peninsula and basically investigate the capability of intrusive kelp application in the food business.

Aroa Lopez-Santamarina et al., [32] review offers a true point of view of the ebb and flows information encompassing the effects of kelp and their inferred polysaccharides on the human microbiome and the significant requirement for additional inside and out examinations concerning this subject. Creature tests and in vitro colonic-mimicking preliminaries researching the impacts of kelp ingestion on human stomach microbiota are talked about.

Ghislain Moussavou et al., [33] review centers around colorectal and bosom diseases, which are significant reasons for malignant growth-related mortality in people. It likewise depicts different mixtures separated from a scope of kelp that has been displayed to annihilate or slow the movement of malignant growth. Fucoidan removed from the earthy colored green growth Fucus has shown movement against both colorectal and bosom diseases. Moreover, we audit the instruments through which these mixtures can instigate apoptosis in vitro and in vivo.

Bahare Salehi et al., [34] present audit gives the most exceptional bits of knowledge into ocean growth research, explicitly tending to its substance synthesis, phytopharmacology, and corrective applications. Kelp is an everyday term for perceptible, multicellular benthic marine green growth. Kelp is probably the biggest maker of biomass in the marine climate and establish a significant piece of the eating routine and conventional medication in many pieces of Asia since ancient times.

Diane Purcell-Meyerink et al., [35] foresee the ocean growth industry requires huge amounts and great kelp unrefined substance that applies tension on the current normal kelp assets. Hydroponics development of ocean growth has developed impressively starting around 2009 to fulfill item needs and to safeguard wild kelp beds that are as yet in danger from over-abuse and environmental change, which has caused expansions in seawater temperatures.

Bruno Moreira Leiteet al., [36] predicted Kelp are notable for their health benefit. As of now, youth weight is an overall developing general medical issue. Three of the central point that adds to this pandemic are unfortunate dietary patterns/inactive, the absence of data on the sustenance worth of food, and the accessibility of caloric thick food with poor healthful substance. In this unique circumstance, well-being advancement through dietary instruction for young kids is of significant importance. The target of this review was to assess the effect of instruction put together mediation with respect to food naming in offspring of five distinct schools in the district of Lisbon.

III. Applications and Methods of Seaweed Cultivation

All through mankind's set of experiences, kelp has been utilized as food, people cures, colors, and mineral-rich composts. Anti-pathogenic activity by green seaweeds, seaweed chocolate, animal food, fertilizers, biotechnology, beauty care products, drug industry, and health benefits is accountable information. Many the women in coastal areas are benefited from seaweed-based cultivation [37-41].The green growth innovation wipes out difficulties related to existing carbon catch techniques.

Figure 5: Bamboo raft method [42].

Figure 6: Bamboo raft method seaweeds for harvesting [42].

Figure 5 and Figure 6 show the bamboo raft method of seaweed cultivation.

IV. Conclusion

This paper presented seaweed applications and their cultivation methods. Minority people, economic growth depends on seaweed harvesting in coastal areas like Ramanathapuram district. Women empowerment, self-employment, development, and many foods, medicine, and cosmetic products are manufactured from seaweeds. In the future, seaweed image color detection and classification are planned to be introduced.

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A Machine Learning-based Model for Implementing the Cybersecurity for Organizations 'Assets

By Dr. Mohammad Mahmoud Abu Omar, Mohammad Awawdeh & Ramze Sanea

An-Najah National University

Abstract- In the current era, cybersecurity problems are one of the critical problems that threaten the organizations' assets, since they may cause a big financial and moral loss. and in the parallel the with the advent of the Machine Learning and Artificial Intelligence techniques, It is important and wise to use these technologies to help in achieving cybersecurity for organizations' assets, due to accurate work of these systems and saving time, effort, and cost. So, this research develops a model that uses machine learning technology to detect the vulnerability in the information security of the organizations' assets to avoid as possible the lack of the information security in organizations' assets and thus avoid the financial and moral loss that such organizations may face.

Index Terms: information security policy, ISP, machine learning, dataset, vulnerable, CART.

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Abstract- In the current era, cybersecurity problems are one of the critical problems that threaten the organizations' assets, since they may cause a big financial and moral loss. and in the parallel the with the advent of the Machine Learning and Artificial Intelligence techniques, It is important and wise to use these technologies to help in achieving cybersecurity for organizations' assets, due to accurate work of these systems and saving time, effort, and cost. So, this research develops a model that uses machine learning technology to detect the vulnerability in the information security of the organizations' assets to avoid as possible the lack of the information security in organizations' assets and thus avoid the financial and moral loss that such organizations may face.

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I. Introduction

Machine learning aims to answer the question of how to create machines that make a decision on their own depending on the learned dataset. It is a mix between computer science and statistics, as well as it is at the heart of artificial intelligence and data science, and is one of today's fastest expanding technological topics.

The information security policy is one of the most critical information security measures. This important directiongiving document, however, is not always easy to create, and its writers struggle with issues such as what defines a policy. As a result, policymakers are forced to rely on existing sources for direction. The many worldwide information security standards are one of these sources.

A dataset is a set of data, usually represented in the form of a table. Each column in the table represents a specific feature, and each row returns to an element of the dataset that is used in the learning phase when building a model.

CART stands for Classification and Regression Tree, can easily handle both numerical and categorical

Author α: Assistant Professor, Faculty of Engineering and Information Technology, An-Najah National University- Nablus, Palestine.
e-mail: mmdabuomar@yahoo.com
Author σ ρ: Student and Cyber Security and Networking expert Faculty of Engineering and Information Technology An- Najah National University- Nablus, Palestine.
e-mails: mohamad.awawdeh2000@gmail.com, ramzesane854@gmail.com

CART stands for Classification and Regression Tree, can easily handle both numerical and categorical variables, but there is tow common disadvantages the first one is CART split one variable at a time, the other one is CART may create unstable decision tree.

II. Research Objectives

- The main goals of the research are to suggest best practices to cover the vulnerabilities that belong to user assets.
- Assisting the user in identifying unknown vulnerabilities that could be destructive and recommending appropriate solutions while keeping the budget in mind.

III. Research Methodology

A suitable dataset is required for any machine learning model, so before implementing any model, it is necessary to provide a suitable dataset that is used to train the machine, and the next step is to split the dataset into two subsets using an appropriate splitting algorithm, the first one being used to train the machine. After that, the appropriate ML algorithm must be chosen and used for dataset exploration and pattern recognition with minimum human intervention. Finally, after the algorithm chooses the second subset, it is used to test and evaluate the model.

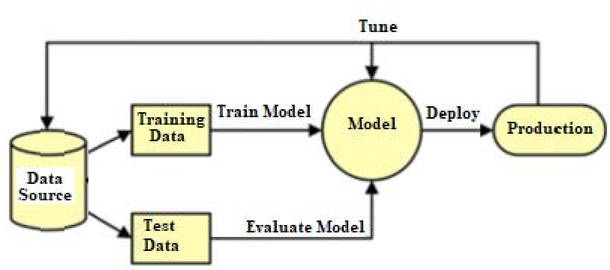

Fig. 1: Supervised learning Workflow

IV. How Does the Model Work

a) Input

Before input, the dataset should be converted to a numerical value so that the algorithm can deal with it and add a new column that contains the unique numerical key points to the solution. Then the numerical dataset will be entered as an input to train and test the model, in addition to the user asset and the budget that he has.

b) Processing

After the dataset enters the model, it should be split into two subdatasets. The first one is to train and the other is to test, and to do so, the machine uses a k-fold algorithm to divide the origenal dataset into test dataset with 0.30 of the dataset at all and the remain data should be the train dataset. The random forest algorithm uses the training dataset by building a number of decision trees. Then combine them to one tree.

c) Output

The final step is to predict the solution key for the user asset, but before that, the machine uses the testing subdataset to evaluate the usage algorithm and the model. So the input data from the user enters into the model and takes a suitable path on the tree that has already been built in the processing phase, and when the machine reaches the leaf that is the prediction that the user needs, the result is converted to the related solution that maps to the prediction key value.

Fig. 2: Work summary

V. Literature Review

ISP is one of the essential documentation in any organization because it o define the rights and responsibilities of information resource users, so to make ISP effective is should be contain the those activity as shown in the figure.

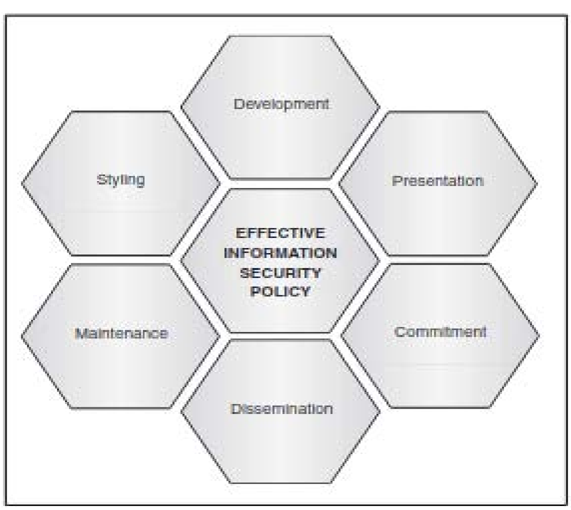

Fig. 3: Supporting activities for an effective information security policy

Styling one of the important factor to develop an efficient ISP so it should be write in clear and consist manner in addition to fit with the organizational culture, the second factor is Development so it should be updated from time to time to be suitable with the organization requirement. the other factor for develop in effective ISP is commitment because when the employee in the organization see the header and all the manger commit to the ISP this means all the employee should Committed to it.

VI. Application Example

After splitting phase the machine calculate information gain for each feature in the splitting datasets to indicate the impurity for each one of them using the following equation.

$$Gain(T,X) = Entropy(T) - Entropy(T,X)$$

- T = target variable
- X = Feature to be split on
- Entropy(T,X) = The entropy calculated after the data is split on feature X

Fig. 4: Information gain

When the machine using random force algorithm it must calculate nodes importance for each created decision tree using the following equation.

$$ni_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)}$$

- ni sub(j) = the importance of node j
- w sub(j) = weighted number of samples reaching node j
- C sub(j) = the impurity value of node j
- left(j) = child node from left split on node j
- right(j) = child node from right split on node j

Fig. 5: Nodes importance

And this lead to calculate the feature importance on a decision tree using the following equation.

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k \in all\ nodes} ni_k}$$

- fi sub(i) = the importance of feature i
- ni sub(j) = the importance of node j

Fig. 6: Feature importance

Then the machine normalized to a value between 0 and 1 by dividing by the sum of all feature importance values as the equation bellow.

$$normfi_i = \frac{fi_i}{\sum_{j \in all\ features} fi_j}$$

Fig. 7: Normalized feature importance

Because the random force algorithm was used, the machine sum all feature's importance value for all decision trees and divided by the total number of trees.

$$RFfi_i = \frac{\sum_{j \in all\ trees} normfi_{ij}}{T}$$

Fig. 8: Actual feature importance

After the machine learn the dataset that entered it well be ready to suggest the key of the solution for the most important vulnerability that the machine see depending on the taken path that the machine take so when the key predicted the check if this key is exist in the interred dataset so if it exist the machine return the solution that related to this key, on other hand if the predicted key does not exist in the dataset the machine try to approximate this key to the nearest value that exist in the dataset and return the solution that related with it.

VII. Conclusion

Machine learning is a wondrous method by which to solve a critical problem. One of them is organization security, so it can help to build an information security policy in a short time with high accuracy.

Assets are the most important thing that the organization has so ot will be secure as possible we can and we can let it more secure by cover the vulnerability for all one of this assets by choose the best solution for all one of it.

In this research the machine learning used to suggest a solution for one vulnerability that belong to the user asset, so the machine depending on both mathematical equation and suitable path in the tree that built in learning phase to choose what one of the vulnerability should choose to suggest the solution for protect against it.

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Clinical Dengue Data Analysis and Prediction using Multiple Classifiers: An Ensemble Techniques

By Veena Kumari H M, Dr. Suresh D S & Dr. Dhananjaya P E

Abstract- Dengue infection is caused by the mosquito Aedes aegypti. According to WHO, 50 to 100 million dengue infections will occur every year. Data-miming techniques will extract information from the raw data. Dengue symptoms are fever, severe headache, body pain, vomiting, diarrhoea, cough, pain in the abdomen, etc. The research work is carried out on real data and the patient data is collected from the Department of General Medicine, PESIMSR, Kuppam, Andrapradesh. Dataset consists of 18 attributes and one target value. Research work has been done on a binary classification to classify dengue positive (DF) and dengue negative (NDF) cases using different ML techniques. The proposed work demonstrates that ensemble techniques of bagging, boosting, and stacking give better results than other models. The Extreme Gradient Boost (XGB), Random Forest by majority voting, and stacking with different meta-classifiers are the ensemble techniques used for binary classification. The dataset is divided into 80% training and 20 % testing dataset. Performance parameters used for the analysis are accuracy, precision, recall, and f1 score, and compared the proposed model with other ML models.

Keywords: dengue fever, aedes aegypti, XGB, stacking, ROC, AUC.

GJCST-D Classification: DDC Code: 025.431 LCC Code: Z696

CLINICALDENGUEDATAANALYSISANDPREDICTIONUSINGMULTIPLECLASSIFIERSANENSEMBLETECHNIQUES

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Veena Kumari H M [α], Dr. Suresh D S [σ] & Dr. Dhananjaya P E [ρ]

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Keywords: dengue fever, aedes aegypti, XGB, stacking, ROC, AUC.

I. Introduction

Dengue fever (DF) is an arthropod-borne viral disease common past three decades. According to WHO, 51-101 million new infections with dengue occur every year in more than a hundred endemic countries [1]. Dengue fever is a severe viral infection with potentially fatal consequences. Dengue fever was originally known as "water poison." The dengue caused by the female Aedes aegypti mosquito is shown in Fig.1

Fig. 1: A Female Aedes Aegypti Mosquito

Author α: Research Scholar, VTU, Belagavi Department of ECE Channabasaveshwara Institute of Technology, Gubbi, Tumkur, Karnataka, India.
e-mail: veenakumari.hm@cittumkur.org
Author σ: Professor Department of ECE Channabasaveshwara Institute of Technology, Gubbi, Tumkur, Karnataka, India.
e-mail: director@cittumkur.org
Author ρ: Professor, Department of General Medicine PES Institute of Medical Science and Research, Kuppam, Andhra Pradesh, India.
e-mail: Dhananjaya_pe@rediffmail.com

In the 1780s, the first clinically recognized epidemics of dengue occurred at the same time in Africa, Asia, and North America. Benjamin Rush was named "break-bone fever" based on the features of arthralgia and myalgia. The dengue epidemic was first reported in Chennai in 1780, the first virologically proven outbreak of dengue fever in India appeared at Calcutta and the East Coast of India in 1963-64. In the 1970s and 1980s, epidemic activity accelerated dramatically, resulting in the widespread of viruses and mosquito vectors and the consequent DENV transmission across the world [2]. The first major DHF epidemic occurred in the Philippines during 1953-1954, continued by a rapid global spread of DF/DHF epidemics. The first major DHF/DSS epidemics in India occurred in 1996, at Delhi and Lucknow, and later extended throughout the country. In India outbreaks of dengue have become more common in many parts. Between 2010 to 2014 incidence of reported cases of dengue was 34.81 per million population. Dengue fever became endemic in Orissa, Uttarakhand, Bihar, Assam, and Jharkhand, in 2010 [3].

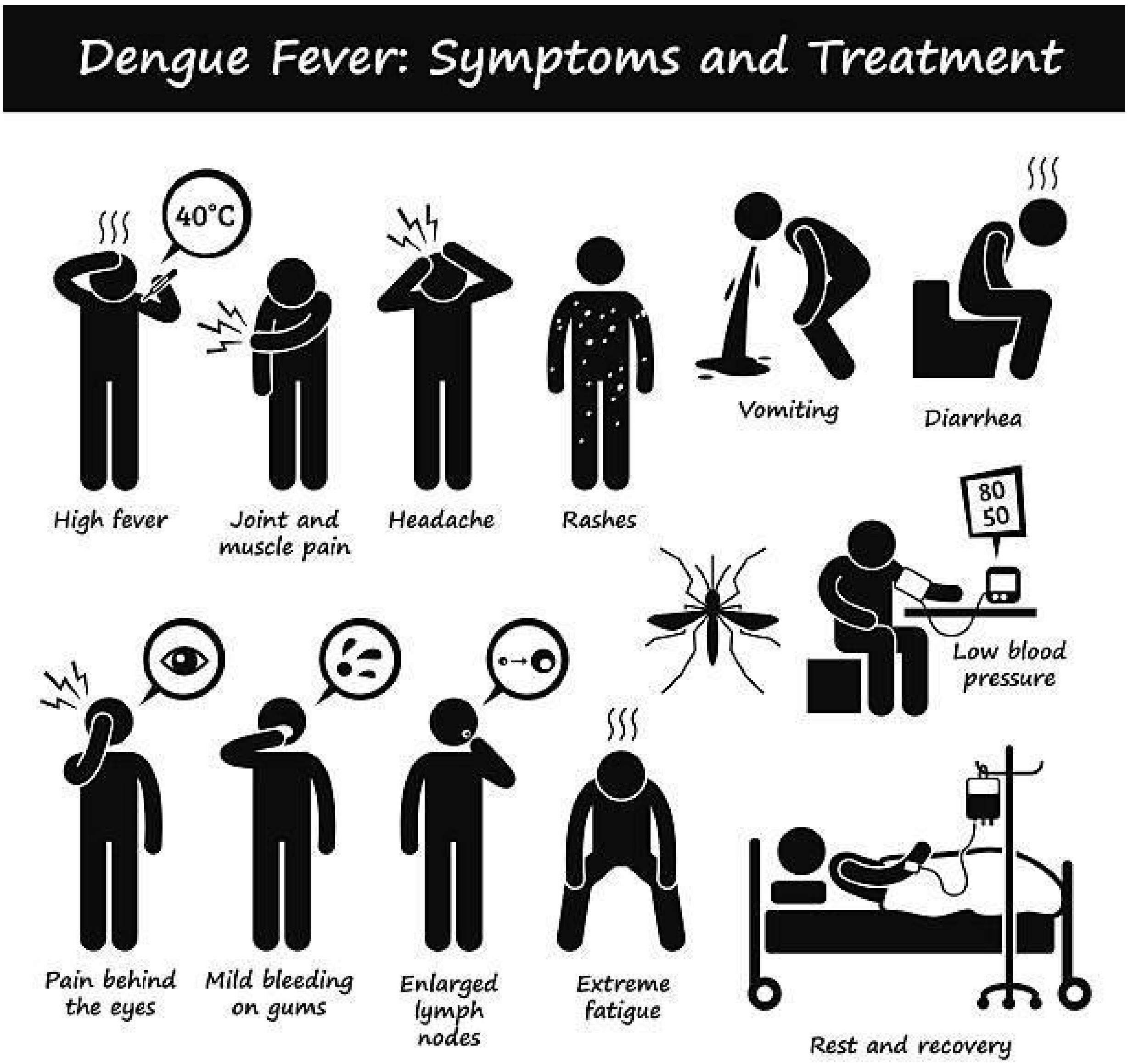

Fig. 2: Pictorial Representation of Dengue Fever Symptoms

According to the World Health Organization, Dengue fever is classified into four types: DENV1, DENV2, DENV3, and DENV4. The incubation period is 2 to 7 days [4]. The Dengue symptoms are high fever, joint and muscle pain, headache, vomiting, rashes, pain behind the eyes, diarrhea, etc. The dengue fever symptoms are shown in Fig.2.

Different ML algorithms are used for dengue fever classification such as NB classifier, K Nearest Neighbour, Decision Tree, Support Vector Machine, and Neural Networks. The proposed model demonstrates ensemble techniques called bagging, boosting, and stacking. The dengue binary classification is based on Extreme Gradient Boost (XGB), Random Forest by

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majority voting, and stacking with different meta-classifiers. The techniques are analysed based on different performance measures called accuracy, precision, recall, F measure, and extended analysis done by the ROC curve, precision-recall curve, and AUC. The organization structure is as follows: Section II explains the work carried out and section III describes the proposed methodology. Performance analysis in section V and Section VI concludes the work.

II. Background Study

Kassaye Yitbarek Yigzaw et al [2] presented a benchmarking platform for the prediction of communicable diseases. Rathi et al [4] studied dengue infection in Rajasthan. The study was based on 100 admitted children and he classified the patients based on their symptoms. Kalayanarooj S [3] demonstrates the clinical appearances of dengue and DHF. Aldallal, A.S [5] explained that data mining techniques are used for the prediction of non-communicable diseases like heart and diabetes. Agrawal et al [7] demonstrated the ensemble approach by using multiple classifiers Ada boost, and a decision tree for the prediction of diabetes. Ghosh et al [10] used multiple classifiers for the sentiment analysis performance assessment. Gupta et al [12] compared different ML approaches for heart disease prediction. Mesafint et al [14] explained ML algorithms for the prediction of HIV/AIDS tests.

III. Proposed Methodology

The ensemble models are Extreme Gradient Boost (XGB), Random Forest (RF) by majority voting, and Stacking, which is based on a combination of heterogeneous classifiers like NB, KNN, and SVM. It is very helpful to consider ensemble techniques [6], for dengue fever diagnosis and prediction. The proposed framework is shown in Fig 3.

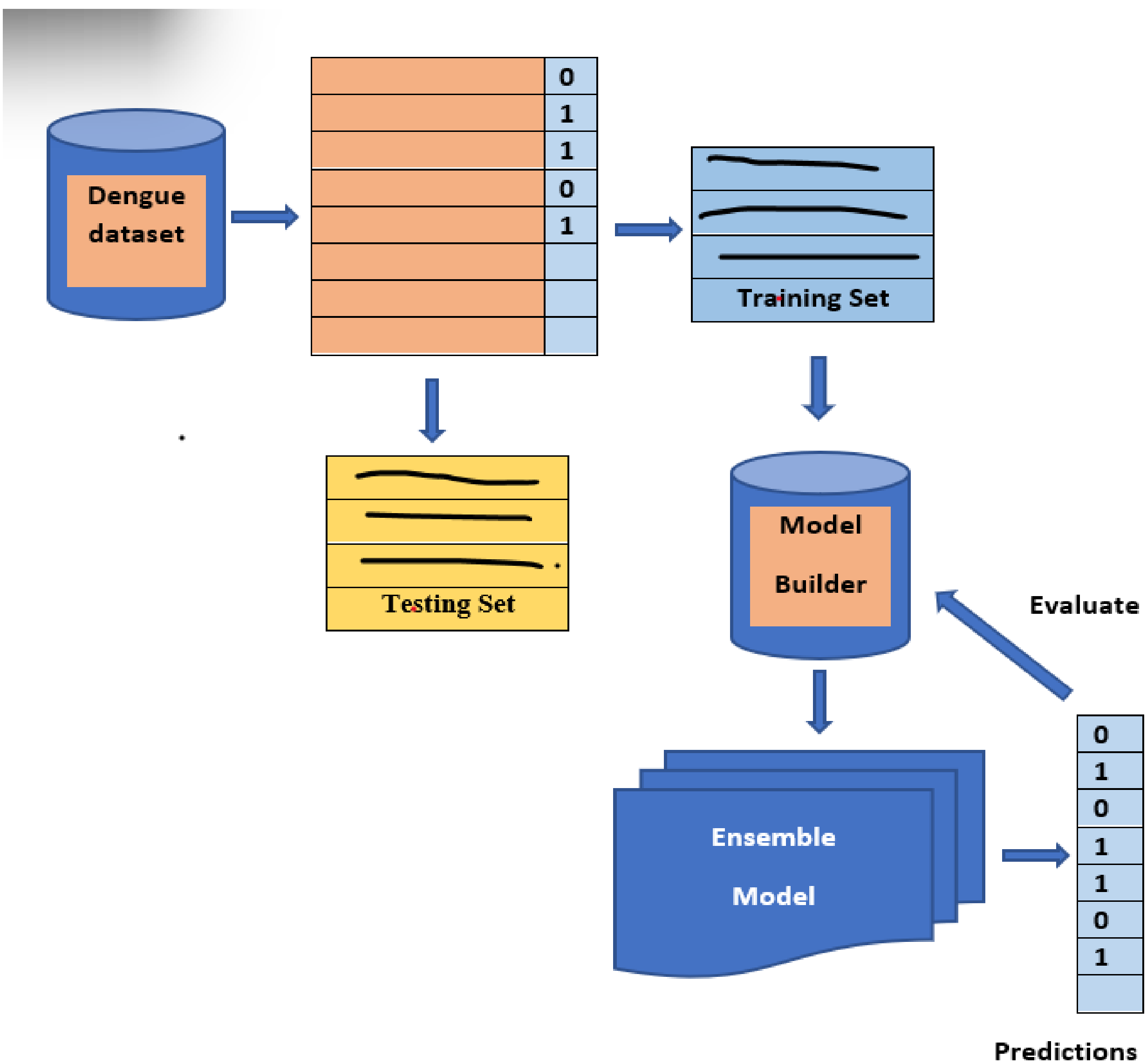

Fig. 3: An Ensemble Frame Work for the Prediction and Evaluation of Dengue Dataset

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a) Data Acquisition and Analysis

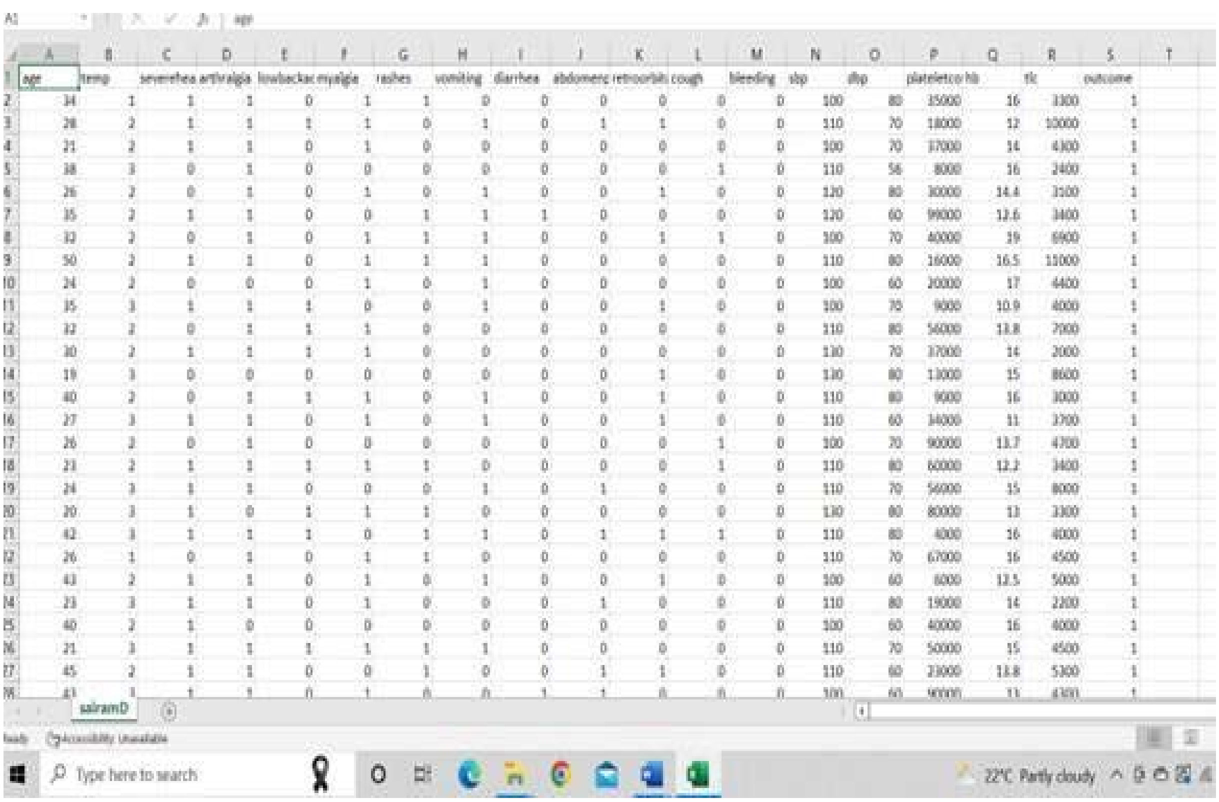
The main aim of data acquisition and the data pre-processing module is to get the Dengue fever dataset and process them into a suitable form for further analysis. Datasets have features/attributes which will finally distinguish the data into patient sick and healthy. The dataset has thirty-eight features and different data types. The dataset is spitted into an 80% training set and a 20% testing dataset. The pre- processing includes feature selection and missing value imputation [8]. The proposed model combines different classifiers such as Naïve Bayes, K -Nearest Neighbor, and Support vector machine. For each classifier, the output is predicted. Each base classifier is used in the ensemble framework by training data to make it useful for the prediction of dengue. Dataset features and target values are known to each classifier, which in turn can predict whether the disease is present or not.

i. *Description of the Dengue Dataset*

The patient data is collected from the Department of General Medicine, PESIMSR, Kuppam, Andrapradesh. The patient is diagnosed in the laboratory using the dengue duo card test shown in fig 4. Dataset consists of 18 attributes and one target value.

Fig. 4: Diagnosis-Dengue Duo Card Test

It consists of 286 instances with 18 attributes and one target. The target consists of dengue patients and Non dengue patients. levels. The numerical value is assigned for each level like 0 for non- dengue patients (NDF), and 1 for Dengue patients (DF). The screenshot of the dataset is shown in Fig.5.



age	temp	severehea	arthralgia	lowbackac	myalgia	rashes	vomiting	diarrhea	abdomenc	retroorbit	cough	bleeding	sbp	dbp	plateletco	hb	tlc	outcome
34	1	1	1	0	1	1	0	0	0	0	0	0	100	80	35000	16	3300	1
28	2	1	1	1	1	0	1	0	1	1	0	0	110	70	18000	12	10000	1
21	2	1	1	0	1	0	0	0	0	0	0	0	100	70	37000	14	4300	1
38	3	0	1	0	0	0	0	0	0	0	1	0	110	56	8000	16	2400	1
26	2	0	1	0	1	0	1	0	0	1	0	0	120	80	30000	14.4	3100	1
35	2	1	1	0	0	1	1	1	0	0	0	0	120	60	99000	12.6	3400	1
32	2	0	1	0	1	1	1	0	0	1	1	0	100	70	40000	19	6900	1
50	2	1	1	0	1	1	1	0	0	0	0	0	110	80	16000	16.5	11000	1
24	2	0	0	0	1	0	1	0	0	0	0	0	100	60	20000	17	4400	1
35	3	1	1	1	0	0	1	0	0	1	0	0	100	70	9000	10.9	4000	1
32	2	0	1	1	1	0	0	0	0	0	0	0	110	80	56000	13.8	7000	1
30	2	1	1	1	1	0	0	0	0	0	0	0	130	70	37000	14	2000	1
19	3	0	0	0	0	0	0	0	0	1	0	0	130	80	13000	15	8600	1
40	2	0	1	1	1	0	1	0	0	1	0	0	110	80	9000	16	3000	1
27	3	1	1	0	1	0	1	0	0	1	0	0	110	60	34000	11	3700	1
26	2	0	1	0	0	0	0	0	0	0	1	0	100	70	90000	13.7	4700	1
23	2	1	1	1	1	1	0	0	0	0	1	0	110	80	60000	12.2	3400	1
24	3	1	1	0	0	0	1	0	1	0	0	0	110	70	56000	15	8000	1
20	3	1	0	1	1	1	0	0	0	0	0	0	130	80	80000	13	3300	1
42	3	1	1	1	0	1	1	0	1	1	1	0	110	80	4000	16	4000	1
26	1	0	1	0	1	1	0	0	0	0	0	0	110	70	67000	16	4500	1
43	2	1	1	0	1	0	1	0	0	1	0	0	100	60	6000	12.5	5000	1
23	3	1	1	0	1	0	0	0	1	0	0	0	110	80	19000	14	2200	1
40	2	1	0	0	0	0	0	0	0	0	0	0	100	60	40000	16	4000	1
21	3	1	1	1	1	1	1	0	0	0	0	0	110	70	50000	15	4500	1
45	2	1	1	0	0	1	0	0	1	1	0	0	110	60	23000	13.8	5300	1
43	3	1	1	0	1	0	0	1	1	0	0	0	100	60	90000	13	4300	1

Fig. 5: The screenshot of the dataset

The target value consists of 140 cases of dengue infected and 146 non-dengue cases among 286 cases. The distribution is shown in Fig.6

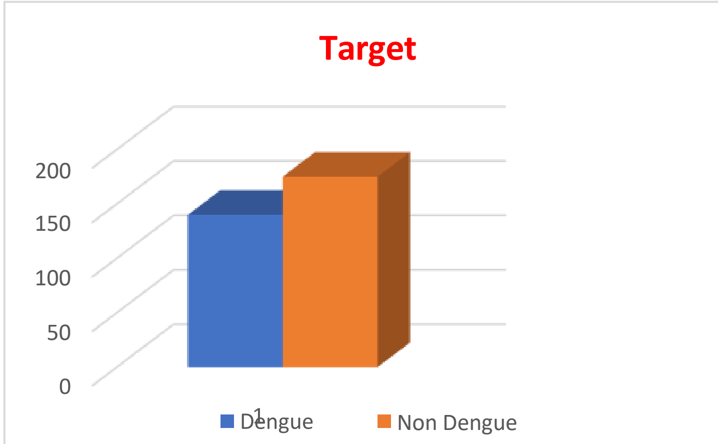


Fig. 6: Distribution of a Target Value

The number of patients having each symptom is listed in Table I and corresponding bar charts explain the importance of each feature [9] are shown in fig.7. Among 140 dengue-infected cases all the patients are suffering from fever,106 headache, 97 and 94 myalgia and arthralgia and 83 low back pain and others.

Table I: Major Clinical Features

Clinical Feature	No. of Patients
Fever	140
Headache	106
Myalgia	97
Arthralgia	94
Low Backache	83
Retro Orb Pain	71
Rashes	65
Vomiting	57
Pain Abdomen	41
Bleeding	39
Cough	30
Diarrhea	25
Sore Throat	16
Breathlessnes	6
Seizures	5

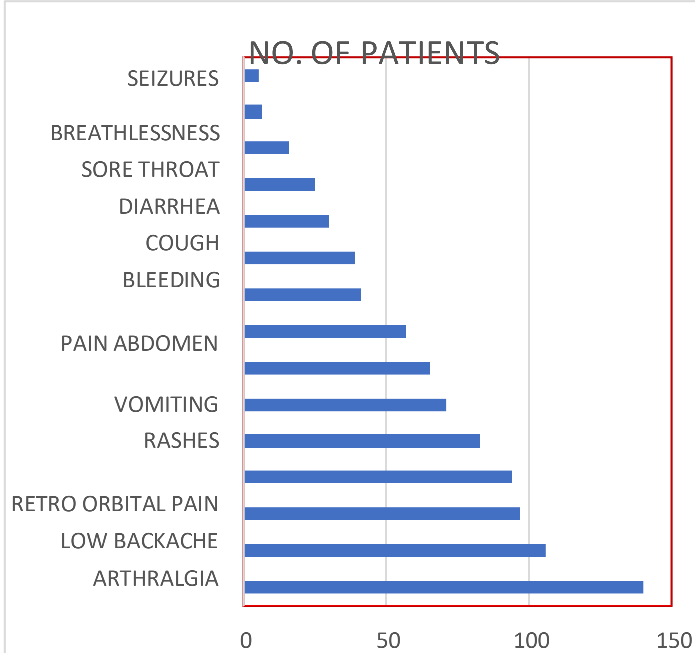


Fig. 7: Bar Chart Representation

b) *Ensemble Methods*

Ensemble means combining multiple models. This approach gives better performance compared to a single model. Thus, a set of models is used for predictions than a single model [7]. The main challenge is to obtain a base model which gives different kinds of errors. If the ensemble technique of bagging, boosting, and stacking are used for classification, high accuracies can be obtained. Bagging creates a different subset of training data from the sample training dataset & the final output depends on majority voting. e.g., Random Forest. Boosting the creation of sequential models by combining weak learners with strong learners and the finally constructed model has the highest accuracy e.g., XGBOOST and ADA BOOST

i. *Random Forest Algorithm*

Random forest is a supervised ML algorithm, used for both classification and regression. Random Forest is a bagging ensemble technique and each classifier in the ensemble model is a decision tree. RF constructs decision trees by a random selection of attributes at each node and then determines the split as shown in fig.8. Each tree votes and their majority vote are used for classification and the most popular class is returned. Random Forest Algorithm can handle the data set containing binary, continuous variables as well as categorical variables in case of regression and classification respectively. RF gives better results for classification problems. Random forest is a simple, fast, flexible, and robust model and it can handle missing values [10, 12].

ii. *XGBoost*

Boosting is a broadly used and highly effective machine learning algorithm. An end-to-end tree boosting system called XGBoost is widely used by data experts. The important factor is its scalability for better accuracy. The system is ten times faster than existing conventional methods. The scalability of XGBoost is due to several algorithm optimizations. Parallel and distributed computing will make learning faster [15].

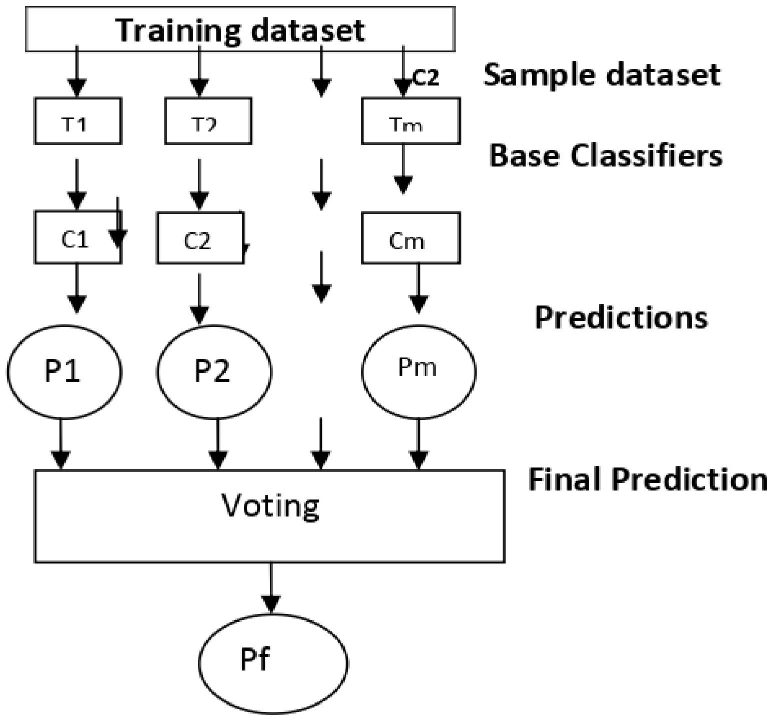


Fig. 8: Random Forest Algorithm Procedure

iii. *Stacking*

Stacking is an ensemble technique, which uses meta-classifiers to learn, the possible way to combine two or more base ML algorithms predictions. The base or level 0 classifiers consists of different ML algorithms and therefore stacking ensembles are generally heterogeneous classifiers. Level 1 classifiers are used as new features to train a meta classifier. An ensemble stacking procedure is illustrated in fig 9. The meta classifier can be any classifier [13]

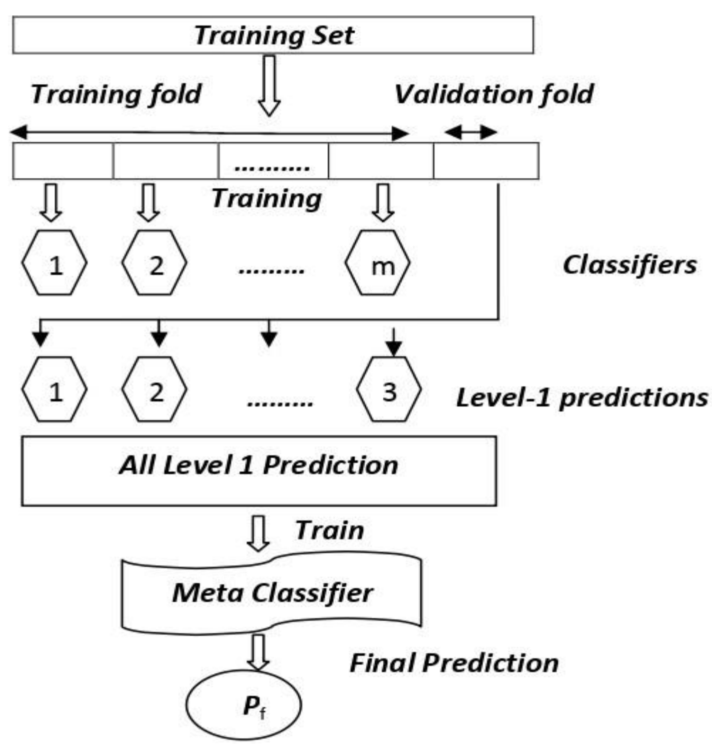


Fig. 9: An Ensemble Stacking Procedure

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In the stacking algorithm, the base (first-level) classifiers are trained by the same set of the training sample, which is used to prepare the inputs for the meta (second-level) classifier, which may cause overfitting. The stackingCVclassifier uses the cross-validation method. The dataset is split into k folds, and k-1 folds are used to fit the level-1 classifier in k successive rounds. In every iteration, the level-1 classifiers are then applied to the remaining subset. The predictions of the base classifiers are then stacked and which is an input to the level-2 classifier.

IV. Performance Evaluation

The clinical dengue fever data set was used to analyse the performance of the ensemble model and to compare it with the other models. The class labels dengue infected (DF) with the dengue not infected (NDF) is replaced with class 1 and class 0 to maintain uniformity [16]. Each dataset is split into training and testing sets. Cross validations of 10-fold are applied. performance measure of each base classifier, as well as the ensemble model, is calculated using a confusion matrix. The base classifiers NB, SVM & KNN are trained first and then they are tested. The proposed research work analysed the performance of the ensemble methods XGB, RF, and Stacking. The metrics are accuracy, recall, precision, and f1-score. The confusion matrix illustrates the actual and predicted classification [15, 17]. The equations (1), (2), (3), and (4), are used to calculate the metrics [17].

Table II: Confusion Matrix

		Actual	
		Dengue Infected	Non-Dengue Infected
Predicted	Dengue Infected	TP	FN
	Non-Dengue Infected	FP	TN

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad \ldots\ldots\ldots\ldots \quad (1)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \ldots\ldots\ldots\ldots (2)$$

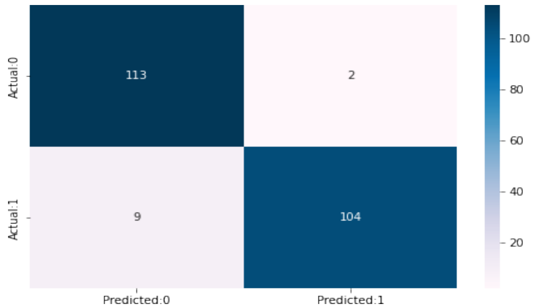
$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \ldots\ldots\ldots\ldots (3)$$

$$F1\ Score — = \frac{2 * Precision * Recall}{Precision + Recall} \ldots\ldots\ldots\ldots (4)$$

The confusion matrix and experimental score of the NB, SVM, KNN, XGB, RF, and Stacking models training dataset and testing dataset are shown in Fig.10.

Training Dataset	Testing dataset
NB	NB

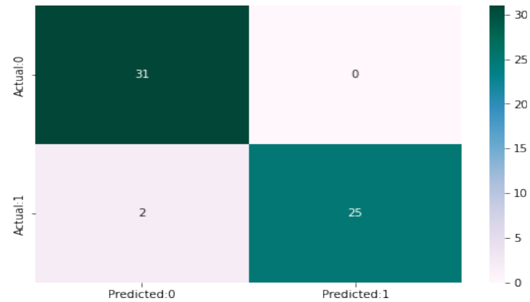
Training Dataset — NB



Accuracy of Naive Bayes model:
95.40

	precision	recall	f1-score
0	0.93	0.98	0.9
1	0.98	0.92	0.95

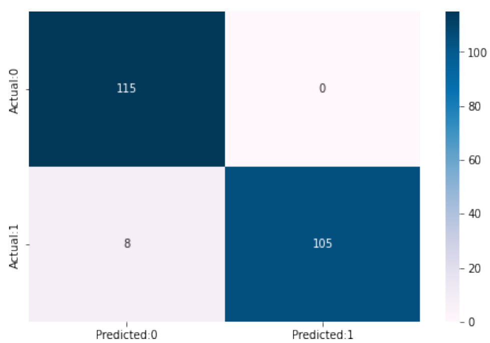
Testing dataset — NB



Accuracy of Naivey bayes :
93.17

	precision	recall	f1-score
0	0.94	0.98	0.96
1	0.97	0.93	0.95

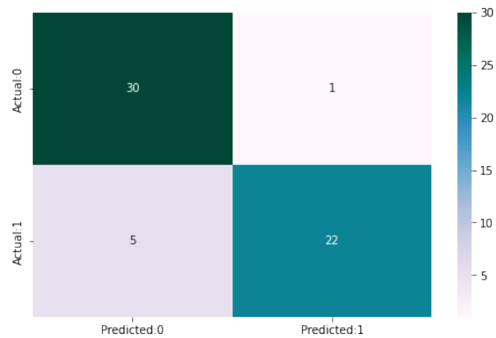
Training Dataset — KNN



Accuracy of K-Neighbors Classifier
:96.49

	precision	recall	f1-score
0	0.93	1.00	0.97
1	1.00	0.93	0.96

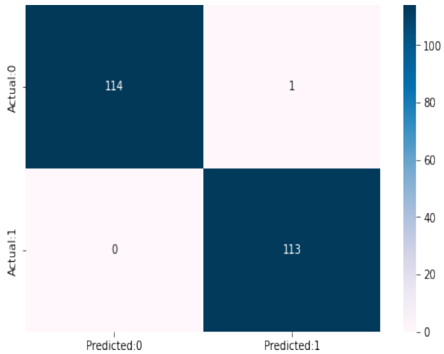
Testing dataset — KNN



Accuracy of K-Nearest Neighbour :
85.66

	precision	recall	f1-score
0	0.86	0.97	0.91
1	0.96	0.81	0.88

SVM



Accuracy of Support Vector Classifier: 97.5

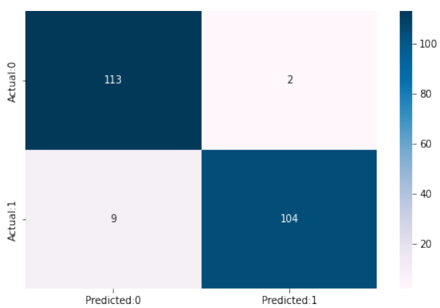
	precision	recall	f1-score
0	0.96	0.98	0.97
1	0.99	1.00	1.00

SVM

Accuracy of Support Vector machine: 89.65

	precision	recall	f1-score
0	0.91	0.98	0.94
1	0.98	0.89	0.93

XGB



Accuracy of Extreme Gradient Boost :98.57

	precision	recall	f1-score
0	0.99	0.97	0.98
1	0.97	0.99	0.98

XGB

Accuracy of Extreme gradient Boost :97.80

	precision	recall	f1-score
0	0.97	0.98	0.97
1	0.98	0.96	0.97

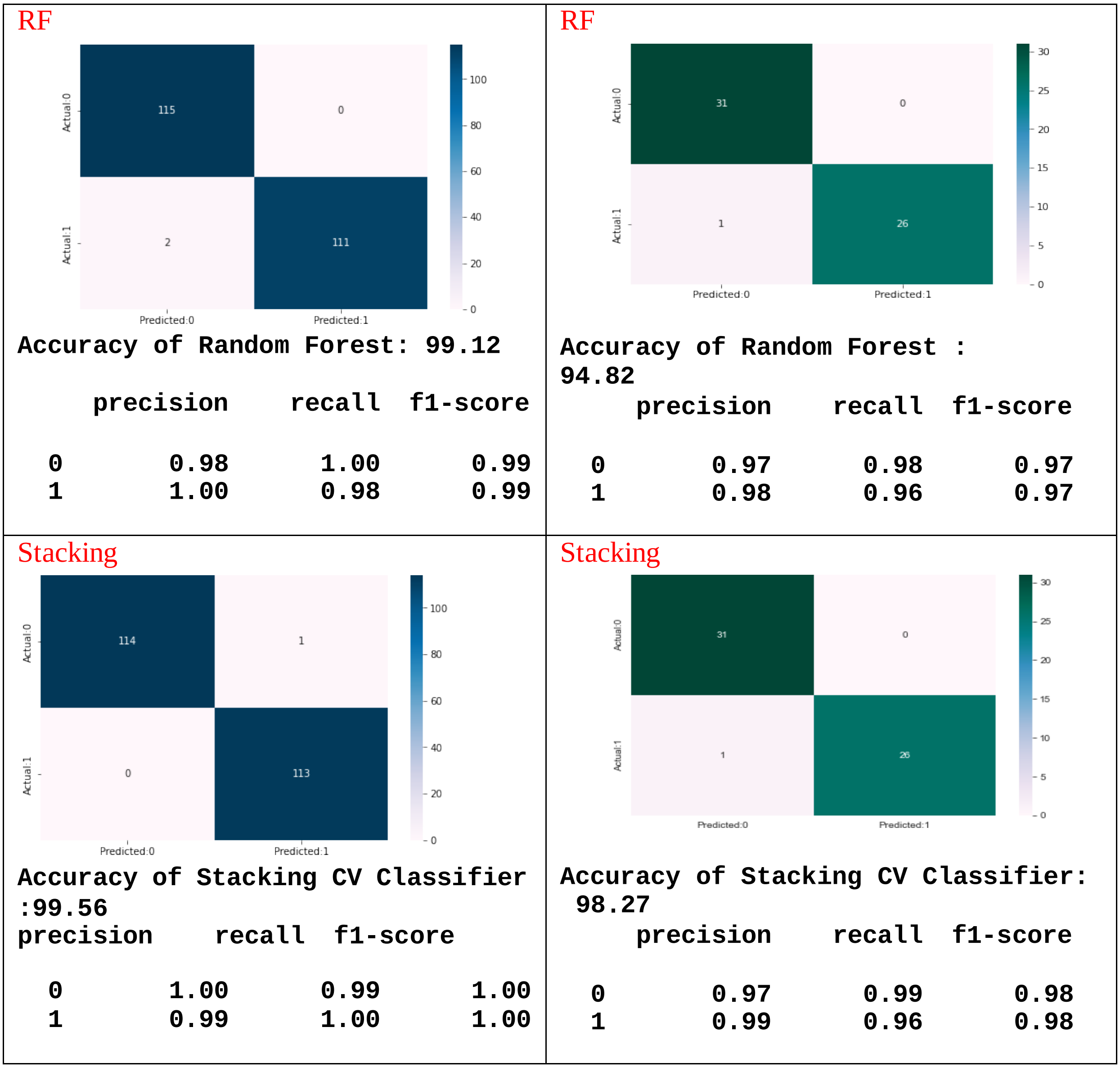


Fig. 10: Confusion Matrix and Experimental Results of Training and Testing Dataset of the Ensemble and Other M Models

Table III: Accuracy of Training and Testing Dataset

Classifiers	Training Dataset	Testing Dataset
NB	95.40	93.17
KNN	96.49	85.66
SVM	97.51	89.65
XGB	98.57	97.80
RF	99.12	94.82
Stacking	99.56	98.27

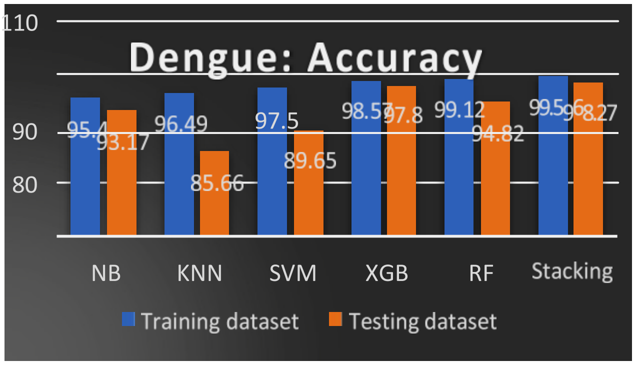


Fig.11: Accuracy Comparison of ML Models

The accuracy comparison of the training and testing dataset is shown in Table III and Fig. 11. The ensemble methods XGB, RF, and Stacking give 98.57%, 99.12%, and 99.56% for the training dataset, whereas 97.80%, 94.82% and 98.27% for the testing dataset. We observed better accuracy for ensemble methods.

Table IV: Precision, Recall and F1 Score of Training and Testing Dataset

Training dataset				
Classifiers		Precision (%)	Recall (%)	f1-score (%)
NB	NDF	93	98	95
	DF	98	92	95
KNN	NDF	93	100	97
	DF	100	93	96
SVM	NDF	96	98	97
	DF	99	100	100
RF	NDF	98	100	99
	DF	100	98	99
XGB	NDF	99	97	98
	DF	97	99	98
Ensemble Stacking	NDF	100	99	100
	DF	99	100	100

Testing Dataset				
Classifiers		Precision (%)	Recall (%)	f1-score (%)
NB	NDF	94	98	96
	DF	97	93	95
KNN	NDF	86	97	91
	DF	96	81	88
SVM	NDF	91	98	94
	DF	98	89	93
RF	NDF	97	98	97
	DF	98	96	97
XGB	NDF	97	98	97
	DF	98	96	97
Ensemble	NDF	97	99	98

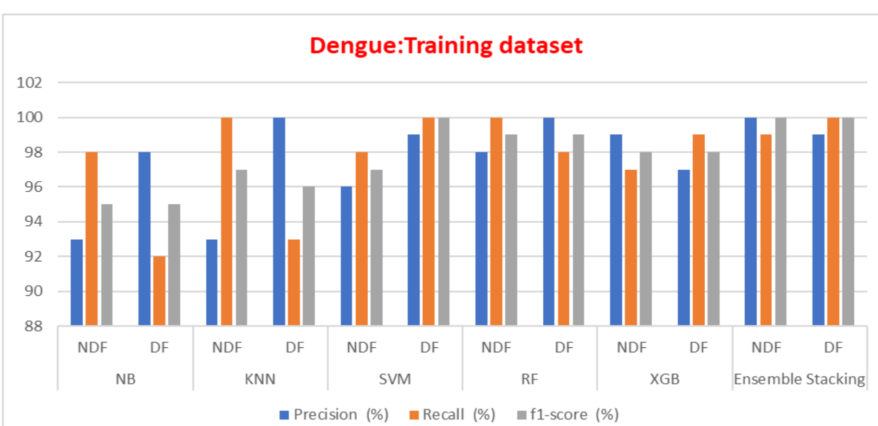


Fig. 12: Training Dataset Precision, Recall and F1 Score Comparison of ML Models

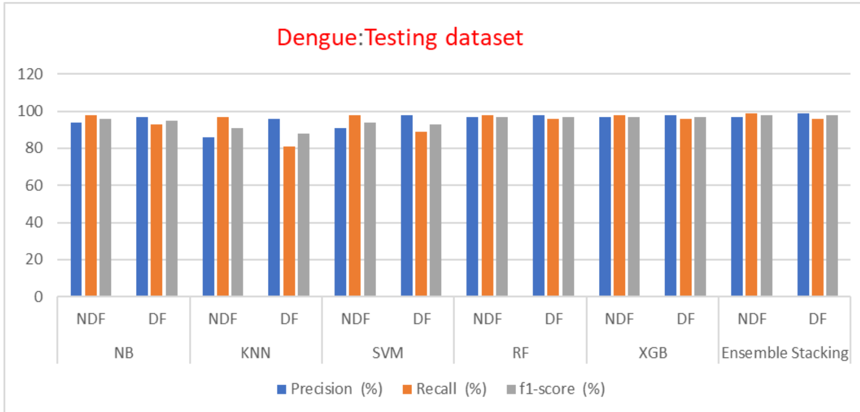


Fig. 13: Testing Dataset Precision, Recall and F1 Score Comparison of ML Models

The precision, recall, and f1 score for training and testing datasets are listed in Table IV and a comparison of an ensemble with other methods is shown in fig 12 and 13, which explains the ensemble methods give better performance for unseen data.

The Receiver Operating Characteristic curve and the Precision-Recall curve is a graphical representation of a, by calculating and plotting the false positive rate (FPR) Vs the true positive rate (TPR) and precision Vs recall for each classifier at various threshold values. The precision and recall curve for both training and testing datasets is shown in fig .14 and fig.15 correspondingly the ROC curve is shown in Fig 16 and Fig 17.

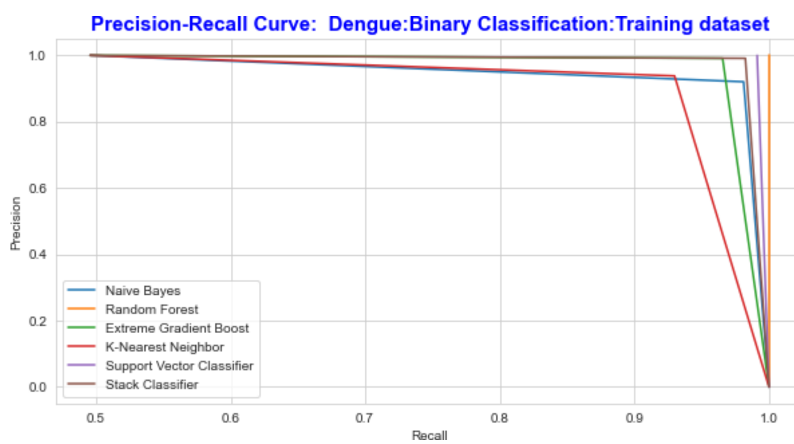


Fig. 14: The Performance Comparison of the Training Dataset by Precision Recall Curve

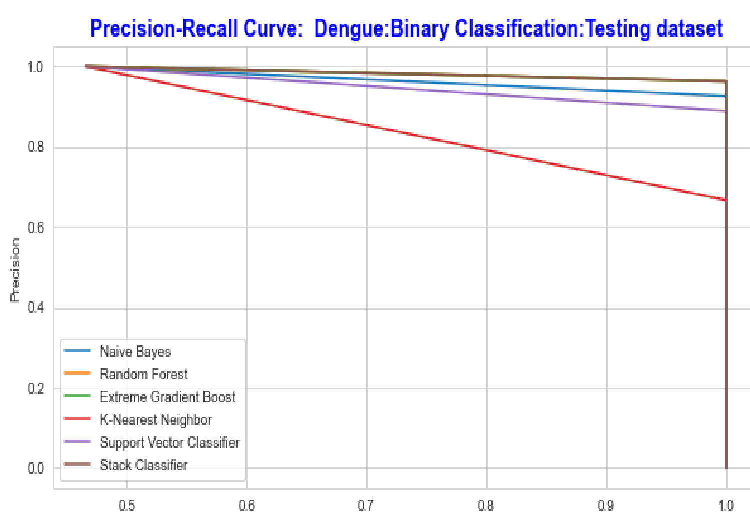


Fig. 15: The Performance Comparison of the Testing Dataset by Precision Recall Curve

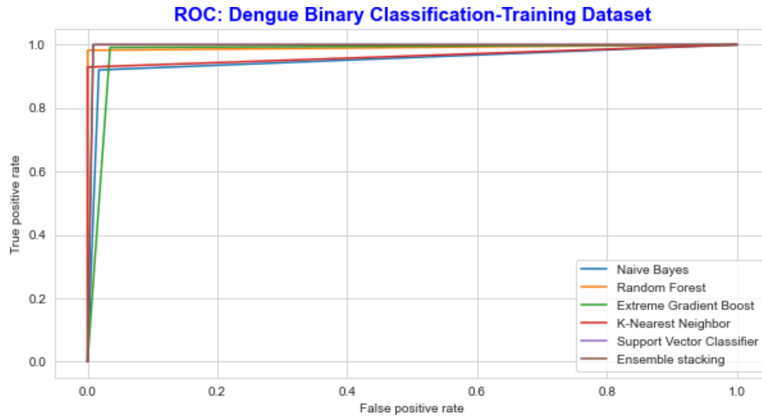


Fig. 16: The Performance Comparison of the Training Dataset by ROC Curve

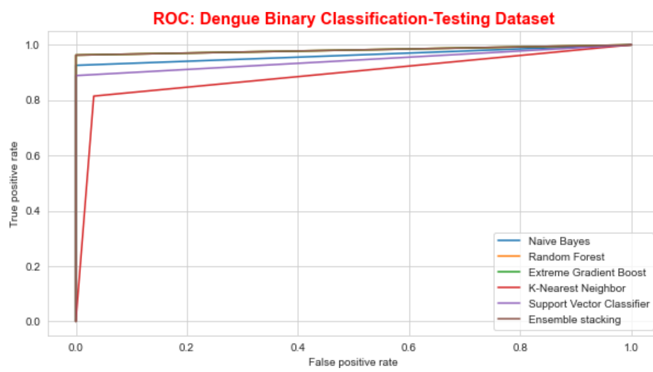


Fig. 17: The Performance Comparison of the testing Dataset by ROC Curve

The ability of the classifier can be measured by Area Under the (AUC) Curve. It is the summary of the ROC curve. High AUC indicates that the performance of the model is better, wherein differentiating between the positive and negative groups. AUC comparison with other classifiers is listed in TABLE IV. The AUC for the proposed ensemble XGB is 97.14% and 97.81% for random forest 98.14% and 99.14%, for stacking 98.14% and 98.68% for testing and Training datasets respectively. As shown in Table III, the AUC values for the datasets lie between 0.97 to 0.99, indicating that the positive class values are correctly distinguished from the negative class values.

Table V: Auc Comparision

Classifier	Testing Dataset	Training Dataset
Auc_Nb	0.9629	0.9514
Auc_Knn	0.8333	0.9342
Auc_Svc	0.9444	0.9956
Auc_Xgb	0.9714	0.9781
Auc_Rf	0.9814	0.9914
Auc_Scv	0.9814	0.9868

V. Conclusion

The main objective of this research work is to the prediction of dengue fever using ensemble techniques. We used bagging, boosting, and stacking methods for prediction and the end results are compared with the NB, KNN, and SVM models. The experimental results prove that Ensemble techniques are the best models for the prediction of dengue fever. The techniques were analysed using performance metrics. The accuracy for the extended boost, random forest with majority voting, and stacking using metaclassifiers gives better accuracy for both the training and testing datasets compared to other models. The extended analysis was done by using the roc curve and precision-recall curve, which explains the performance of the models. The Area under the curve lies between 0.97 to 0.99. The ensemble models are the better models for the prediction of dengue-infected patients.

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Application of Convolutional Neural Network in the Segmentation and Classification of High-Resolution Remote Sensing Images

By Dr. E. Kesavulu Rreddy
S. V. University

Abstract- Numerous convolution neural networks increase accuracy of classification for remote sensing scene images at the expense of the models' space and time sophistication. This causes the model to run slowly and prevents the realization of a trade-off among model accuracy and running time. The loss of deep characteristics as the network gets deeper makes it impossible to retrieve the key aspects with a sample double branching structure, which is bad for classifying remote sensing scene photos. We suggest a dual branch inter feature dense fusion-based lightweight convolutional neural network to address this issue (BMDF-LCNN). In order to prevent the loss of shallow data due to network development, the network model can fully extricate the data from the current layer through 3 x 3 depthwise separable method is structured and 1 x 1 standard pooling layers, identity sections, and fusion with the extracted features out from preceding stage through 1 x 1 standard pooling layer.

Keywords: *remote sensing, convolutional neural network, standard convolution, feature extraction.*

GJCST-D Classification: *DDC Code: 621.3678 LCC Code: G70.4*

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Strictly as per the compliance and regulations of:

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Abstract- Numerous convolution neural networks increase accuracy of classification for remote sensing scene images at the expense of the models' space and time sophistication. This causes the model to run slowly and prevents the realization of a trade-off among model accuracy and running time. The loss of deep characteristics as the network gets deeper makes it impossible to retrieve the key aspects with a sample double branching structure, which is bad for classifying remote sensing scene photos. We suggest a dual branch inter feature dense fusion-based lightweight convolutional neural network to address this issue (BMDF-LCNN). In order to prevent the loss of shallow data due to network development, the network model can fully extricate the data from the current layer through 3 x 3 depthwise separable method is structured and 1 x 1 standard pooling layers, identity sections, and fusion with the extracted features out from preceding stage through 1 x 1 standard pooling layer. Additionally, we suggest a down sampling structure that makes use of the pooled branching to down sample and the convolution branching to make up for the pooled features in order to extract the shallow characteristics of the network more effectively. Four open and difficult remote sensing images scene data sets were used for the experiments. The experimental findings show that the suggested method realises the trade-off among model accuracy and system running speed and has better classification accuracy and reduced model complexity than various state-of-the-art classification techniques.

Keywords: remote sensing, convolutional neural network, standard convolution, feature extraction.

I. Introduction

In applications including urban development, land-use planning, infrastructure construction management, natural disasters, and crisis management, urban land-use classification is crucial [1]. The rate of change in land usage increases with the nation's rate of growth. Costly, labor-intensive, and time-consuming are land-use surveys [2]. China conducts a national land-use survey every ten years. High-resolution remote sensing processing technologies are being developed, which may assist planners in quickly and affordably gathering comprehensive land-cover data [3]. Deep convolutional neural networks (DCNNs), for instance, might fully achieve the classification of urban land-use by automatically extracting species-specific information from remote sensing photos. According to current criteria for land-use classification, one typical class may include more than one type of item. Each might also contain various objects that adhere to various standards. The Land-Use Standard of the 2nd and 3rd National Land-Use Resource Surveys, for instance, has various contents. Convolutional neural networks (CNN) trying to identify high-resolution remote sensing images are faced with significant difficulties by the complex spatial and textural patterns in one class [4]. Early FCN-based models had a limited ability to reconstruct spatial information despite acquiring rich contextual data and suffered from loss of high-frequency details, blurring boundaries, and difficulty identifying features.A skip connection was introduced to the networks to address this issue. By combining the multi-layer feature maps from the encoder with the decoder structure for incremental up sampling, Ronneberger et alU-Net.'s.

Architecture created high-resolution feature maps [5]. The classification effects of object boundaries are improved by the merging of high- and low-level semantic information. Later, Yu and Koltun added atrous convolution to fully convolutional networks (FCN), which could maintain the resolution of a featured image, expand the receptive field to capture multi-scale context information, and boost the precision of semantic segmentation using spatial information in the images [6]. Spatial Pyramid Pooling (SPP) [7] has been widely used to better capture information about the global context.

To take advantage of the potential of global context information, Zhao et al. used a pyramid pooling module to aggregate the context of several regions [8]. In order to gather multi-scale information, Chen et al. implemented pyramid-shaped atrous pooling in spatial dimensions [9] and piled up atrous convolution [10] with various atrous in cascade or in parallel. The resolution in the scale axis dimension was insufficient for Atrous Spatial Pyramid Pooling (ASPP) [9] to precisely extract target features from remote sensing images, therefore it still had certain drawbacks (RSIs). In order to effectively identify complicated situations while maintaining the model's size, Yang et al. introduced densely-connected Atrous Spatial Pyramid Pooling (DenseASPP) [12], which was able to cover a broader scale of the feature

Author: Assistant Professor Department of Computer Science S. V. University, Tirupati, Andhra Pradesh India.
e-mail: ekreddy@svuniversity.edu.in

map and acquire more intensive receptive field information. A labor-intensive foundation, including well-tagged remote sensing image labels for the most recent urban land cover types under distinct categorization standards, must be built in order to address the inherent difficulties in the present classification methods used to classify urban land use. Combining algorithms to produce higher-level sematic class images is another effective way to replace the original photos in labor-intensive tasks. We proposed a double-layer deep convolutional neural network called DUA-Net that mainly combined two networks with different advantages, U-Net and DenseASPP, into a parallel structure in order to take into account the characteristics of urban land-use types, which contain multiple elements in one type. The methodology utilised in this study can produce a larger, continuous block of land use classification for urban areas. It can considerably cut down on operation durations and manual interactions when using the image of this classification result as the input for artificial fine classification, which can increase efficiency. Additionally, with the aid of vector data, we can fully utilise the same standard to categorise the photographs taken at various points in time in order to study the changes in land types at various times.

High resolution remote sensing images are being used in a variety of applications, including the classification of remote sensing scenes [1], hyperspectral image classification [2], change detection [3, 4], geographic image classification, and the classification of land use [5, etc. However, image categorization presents significant challenges due to the intricate spatial patterns and geographical structure of remote sensing images. Therefore, it is crucial to effectively comprehend the semantic information of remote sensing photographs [6]. The goal of this study is to identify a straightforward and effective lightweight network model that is capable of quickly and reliably classifying remote sensing scene photos. Researchers have suggested a variety of techniques for efficiently extracting visual information.To begin with, manually created feature descriptors including colour histograms, texture descriptors, local binary mode, GIST, directional gradient histograms, bag-of-visual words (BOVW), etc. were used to extract picture features. Researchers then proposed some unsupervised feature learning techniques that can automatically extract shallow detail features from images in order to address the drawbacks of the method of manually extracting features. These techniques include principal component analysis (PCA), sparse coding, autoencoder, Latent Dirichlet allocation, and probabilistic latent semantic analysis. For the extraction of shallow picture information, the two feature extraction techniques mentioned above work quite well. However, the extraction of high-level features from images using these techniques is challenging, which restricts the development of classification accuracy.

Researchers have proposed convolutional neural networks, which have the ability to automatically extract significantly discriminative features from images, as a way to get around the limitations of existing methods. Since then, the model based on convolution neural networks has replaced other techniques as the industry standard for classifying remote sensing scene images. A lightweight convolution neural network may now achieve a balance between the speed of model operation and the precision of model classification thanks to advancements in convolution neural networks. Lightweight networks have currently been used for a variety of applications, including target recognition, image segmentation, and classification. The fire module, which separates the initial basic convolution layer into an extrusion layer and an expansion layer, was proposed by SqueezeNet. The extension layer is made up of a set of continuous 1 x 1 convolution and 3 x 3 convolution channels, whereas the extruded layer is made up of a continuous set of 1 x 1 convolution channels. The Google team's MobileNet has three iterations: V1, V2, and V3. In order to divide the regular convolution into depthwise convolution and 1 x 1 convolution, MobileNetV1 employs depthwise separable convolution. This significantly decreases the number of network parameters and, to some extent, increases accuracy. An inverse residual module and a linear bottleneck structure were presented by MobileNetV2. The convolution of 1 x 1 for ascending dimension, 3 x 3 depthwise separable convolution for feature extraction, and 1 x 1 convolution for dimension reduction were all applied to this bottleneck structure in that order. With the addition of the SE module and the use of neural structure search, MobileNet V3 examines the network's setup and parameters [10]. An extremely effective convolution neural network architecture called ShuffleNet was created for mobile devices with constrained processing resources. Compared to some sophisticated ones with comparable accuracy, the design only requires two operations—group convolution and channel mixing—which significantly lowers the computation time.

II. Related Works

Remote sensing picture databases are being produced in greater numbers. These datasets use a variety of land cover and land use categories, and Castillo-Navarro et al. [14] have developed datasets that cover various scenes to increase surface coverage. Additionally, the labels that have been applied to the datasets vary [15]. For instance, BigEarthNet [17] and SEN12MS [16] both give image-level labels and pixel-level labels, respectively, and both datasets with varying scene categories can only be used for particular semantic segmentation applications. For instance, LULC has hundreds of fine-grained semantic classifications that may be further broken down into categories like highways, buildings, cars, the countryside, cities, etc.

The circumstances that can show the relationship between the content of interest and its surroundings are rarely taken into account, and many datasets simply ignore the relationships within and across semantic classes [18]. Rich and detailed geometric features, texture information, and geospatial data are all present in high-resolution RSIs [19]. For land-use classification, the features extracted from these images can be interpreted with high accuracy. Pixel-based image analysis, object-based image analysis, and pixel-level semantic segmentation have all been used to classify the land use of RSIs [20]. Low-resolution remote sensing photos have historically been classified primarily using spectral data from remote sensing photographs.

Because the spectral features of pixels, which lack textural features and structural data, are unable to fully capture the characteristics of land-use kinds, the classification results for complicated land-use types, such as residential land and wasteland, are frequently less than optimal [21]. Similar pixels in different land-use types on residential and industrial land may exist. Some strategies, like Transfer Learning [22], Active Learning [24], and others, have been developed with the goal of increasing the size and enhancing the effectiveness of training datasets. Ammour et al. [25] merged two asymmetric networks for data domain adaption and classification, projected the two networks to the same feature space, and performed post-training for the weight coefficient adjustment method of the two networks. They employed a pretraining network for feature extraction.

Migration tests were conducted by Zhou et al. [26] using data from the same sensor at various dates. Additionally, they created a very difficult migration experiment that tested the efficacy of feature extraction and migration structure and was performed on hyperspectral remote sensing data from various viewpoints. The object-oriented classification approach [27] takes into account the correlation information between pixels and the internal texture features of ground objects while leveraging the spectrum information of RSIs [28] to make up for the inadequacies of conventional pixel-based classification methods. However, feature descriptions are generally incomplete, and the data collected is frequently insufficient to assist the characterization and identification of ground objects.

Deep learning overcomes the limitations of artificial features, directs object categorization, and achieves pixel-level land-use classification of RSIs by mastering the shape and texture aspects of various objects. Deep learning has been used extensively in RSIs for land-use classification. To automatically train the representative and discriminative features in a hierarchical way for land-use scene classification, deep filter banks were proposed to integrate multicolumn stacked denoising sparse autoencoders (SDSAE) with Fisher vectors (FV) [29]. A land-use classification framework for photographs (LUCFP) was presented by Xu et al., and it was effectively used to automate the verification of land surveys in China [30]. Adaptive hierarchical image segmentation improvement, multilevel extraction of features, and multiscale supervised deep - learning models were integrated to accurately produce detailed maps for disparate urban areas from the fusion of the UHSR ortho mosaic and digital elevation model, taking into account the high-level details in an ultrahigh-spatial-resolution (UHSR) unmanned aerial vehicle (UAV) dataset (DSM). Excellent potential was shown by this framework for the thorough mapping of varied urban areas [31]. Another cutting-edge hybrid approach is multi-temporal relearning using convolutional long short-term memory (LSTM) models. It integrates post-classification relearning with locational semantic segmentation and is effective at categorising complex LULC maps with multitemporal VHR pictures [32].

III. Methodology

a) Proposed Architecture

Figure 1 depicts the model's overall structure, which is broken down into nine sections. We suggest a feature extraction structure for the network's shallow layers in the first and second groups. The maximum pool layer is used for down sampling in the third group, where standard convolution and depth-wise separable convolution are combined. This reduces the spatial dimensions of the input images and lowers the danger of overfitting from irrelevant features. The majority of representative features from remote sensing image are extracted by groups 4 through 8. For the purpose of extracting richer feature information, Groups 4 through 7 use the proposed dual branch multi-level feature intense fusion method.

To extract deep-level features from Group 8, we sequentially applied 1 x 1 standard convolution, 3 x 3 standard convolution, and 3 x 3 depth wise separable convolution. The multilevel characteristics are fully exchanged and fused on the basis of double branch fusion, which not only increases classification accuracy but also significantly speeds up the network and achieves a balance between accuracy and speed. The number of convolution channels in Groups 5 and 8 is also increased to 256 and 512, respectively, in order to extract more features. The feature information generated by the final fusion is used to calculate the likelihood of each scene category, and Group 9 is used for classification. Each layer in deep feature extraction structures from Group 4 to Group 7 may fully extract the

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data of the current layer through three branches, including Identity, 1 x 1 standard convolution, and 3 x 3 depth wise separable convolution. Additionally, the shallow information loss caused by network deepening can be successfully avoided by merging the features retrieved by 1 x 1 standard convolution with each prior layer. Batch normalization (BN) can speed up training and use a greater learning rate while reducing the network's reliance on parameter initialization. Additionally, there are far less remote sensing photos available for training compared to the natural image data collection.

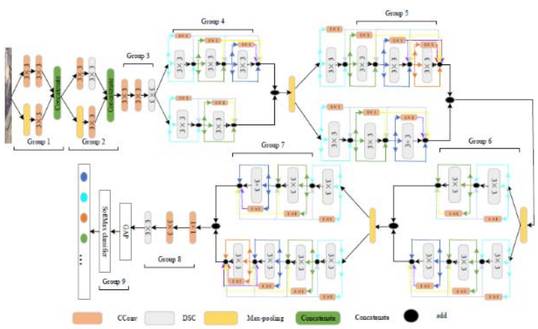

Figure 1: Proposed Architecture

In order to gather spatial information, boundary information, multi-scale contextual information, and global contextual information, our proposed model utilised parallel modules. As a result, it was able to reduce border ambiguity and class imbalance, address the inaccurate, fragmented single element classification in urban land-use semantic segmentation, and increase urban land-use classification accuracy. This section showed the DUA-suggested Net's architecture for classifying urban land use. The essential components of the suggested design, including the U-Net module, DenseASPP module, and Channel Attention Fusion module, were then thoroughly explained. In this study, U-Net and DenseASPP, two different DCNNs, were used to build the distributed system of DUA-Net, which fully utilised the various benefits of these two types of networks in the semantic segmentation of RSIs. The suggested framework has three components, as seen in Figure 1: a backbone network, a parallel extracting features module, and a feature fusion module. First, the VGG16 network is introduced as the foundation for extracting the features in U-Net and DenseASPP. Second, we use the U-Net module and DenseASPP module to simultaneously collect various semantic pieces of information due to the complexity of land-use type, structure, and geographic distribution of abnormality.

For more specifics, the DenseASPP module aggregates semantic information at various scales to capture multi-scale contextual information and global contextual information, and the U-Net module fuses high-level and low-level semantic information to improve the extraction of spatial and boundary information. Then, to address the issue of improper segmentation caused by comparable characteristics of similar categories, the feature maps output by the U-Net module and DenseASPP module were fused in the channel dimension through the attention mechanism in the Channel Attention Fusion module. The segmentation results were then produced by convolution with a convolution kernel size of 1 x 1 after the feature vectors had been mapped to the necessary number of classes. The DenseASPP module was introduced as the feature extractor in order to gather multi-scale contextual information as well as global contextual information in RSIs. In order to achieve integration at various levels with various dilation rates, DenseASPP employs the concept of dense connection and arranges numerous convolution layers in a cascade manner. Without significantly growing the model size, this organising approach not only covers a broader scale, but also covers it intensively. To gather semantic information from various scales, this work specifically exploited dense connections to send the output of each atrous convolution layer to all previously unvisited atrous convolution layers.

Additionally, the atrous convolution dilation rate at each layer increased layer by layer, enlarging the receptive field while maintaining the same level of feature map resolution. The layer with the lowest dilation rate among them was positioned in the lower layer, and the layer with the highest dilation rate was positioned in the upper layer. The outputted feature map from the multi-scale convolution process was the last step. The connection between feature channels is typically ignored by traditional techniques, and thus exhibit low sensitivity to critical information characteristics throughout the fusion process.

We used the channel attention method to successfully combine the feature maps from the U-Net module and the DenseASPP module. This fusion module achieved the automatic selection and weight assignment of attention regions, then increased output feature quality by using SENet to learn the correlation between various feature channels (and to boost the extraction of significant features). In particular, its primary operations were concatenation, squeeze, and excitation. The shallow features of the network are intended to be extracted by the first and second sets of down sampling structures. The impact of down sampling on network performance during the shallow feature extraction phase is significant. Down sampling is the process of scaling down the complex feature map to maintain the image's primary features while reducing the spatial size of the image. Having a greater number of pooling layers is one of the primary techniques for down sampling in deep convolution neural networks.

IV. Results and Discussion

Three of the down sampling techniques indicated in Section IIB are utilised in the first and second levels of the network to verify the effectiveness of our suggested down sampling techniques. Two datasets, UC and RSSCN, were employed for the experiments, and the OA and Kappa were used as evaluation metrics. According to Figure 2, the first and third convolution steps for the Conv-Downsampling (CD) are 1, while the second and fourth convolution steps are 2. The convolution kernels for the pooling down sampling (Max pooling-Downsampling, MD) are all 3 x 3, with convolution steps of 1 x 1. The pooling step size and maximum pooling size are both 2.On the two datasets, pooling down sampling had poorer classification accuracy and Kappa values than convolution down sampling. Convolution down sampling in deep networks produces superior non-linear performance than pooled down sampling, which is the reason. On the 80/20UC and 50/50RSSCN datasets, the suggested down sampling methods have classification accuracy scores of 99.53% and 97.86%, respectively, and Kappa values of 99.50% and 97.50%, which are greater than those of the other two down sampling methods.

This demonstrates once again how much more accurately the multi-level features dense fusion technique can identify remote sensing scene photos. In this section, three types of visualisation, including grad cam, t-distribution random neighbour embedding (T-SNE), and randomly picked and tested are explained and examined in order to more clearly demonstrate the effectiveness of the suggested method. Through a visual thermal map, the grad cam presents the retrieved features in order of significance. The most comprehensive spatial and semantic information is found in the final layer of a convolution neural network.

Grad Cam creates an attention map to highlight key portions of an image by fully utilizing the features of the last layer of convolution. In this experiment, some remote sensing scene photos from the RSSCN collection of "Industries," "Fields," "Residences," "Grass," and "Forests" are randomly chosen. Figure 2 compares the thermal diagram visualization outcomes of the enhanced BMDF-LCNN approach with the baseline LCNN-BFF method.

Figure 2 shows that, for "Industries" scenarios, the LCNN-BFF approach transfers the attention to the highway rather than accurately focusing on the factory region, whereas the proposed BMDF-LCNN method accurately focuses on the industrial area. While the BMDF-LCNN approach is well focused on the target region, the LCNN-BFF model's focused areas for the "Fields" and "Grass" scenarios both showed a partial deviation, ignoring the similar surrounding targets and searching with few objects. Additionally, the LCNN-BFF method's restricted coverage and inability to fully extract the target for scenario regions like "Residence" and "Forests" has an impact on the classification accuracy. However, in these cases, the suggested BMDF-LCNN approach can get a comprehensive region of interest. Next, we use t-distribution random neighbor embedding to illustrate the classification results on the UC (8/2) and RSSCN (5/5) datasets (T-SNE). High-latitude characteristics are mapped by T-SNE to two- or three-dimensional space for visualization, which is a very effective way to assess the classification effect of the model.

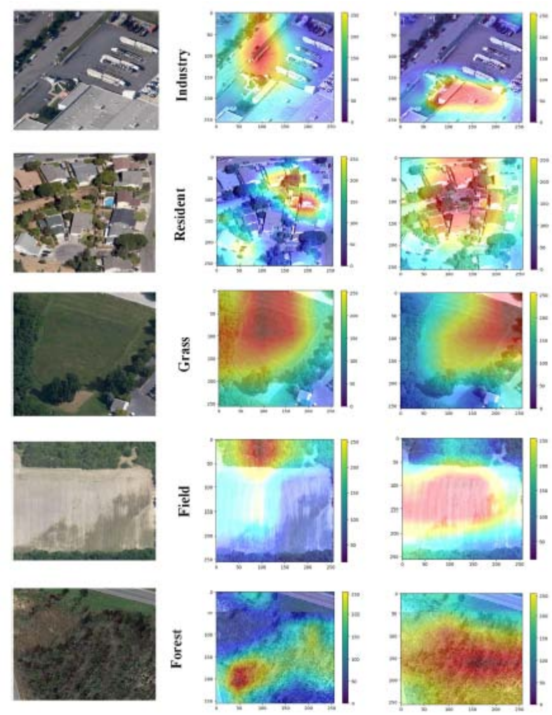

Figure 2: Results of Convolutional Neural Network Segmentation and Classification

V. Conclusion

A lightweight network based on the dense fusion of dual-branch, multi-level features is proposed for the categorization of remote sensing scene photos. A fresh down sampling technique was also developed to gather more accurate feature data. The information of the current layer can be fully extracted and fused with the features extracted by 1x1 standard convolution in the previous layer using the three branches of 3 3 depth wise separable convolution, 1 x 1 standard convolution, and identity in the network. This effectively realizes the information interaction between different levels of features and improves the classification performance and computational speed of the model. The suggested model still requires development. Due to the generation of certain redundant data during multi-level feature heavy fusion, the computational complexity rises. Future

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research should discover a technique that can fuse data selectively, limit the production of redundant data, and further develop a lightweight model that combines speed and accuracy.

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1. Choosing the topic: In most cases, the topic is selected by the interests of the author, but it can also be suggested by the guides. You can have several topics, and then judge which you are most comfortable with. This may be done by asking several questions of yourself, like "Will I be able to carry out a search in this area? Will I find all necessary resources to accomplish the search? Will I be able to find all information in this field area?" If the answer to this type of question is "yes," then you ought to choose that topic. In most cases, you may have to conduct surveys and visit several places. Also, you might have to do a lot of work to find all the rises and falls of the various data on that subject. Sometimes, detailed information plays a vital role, instead of short information. Evaluators are human: The first thing to remember is that evaluators are also human beings. They are not only meant for rejecting a paper. They are here to evaluate your paper. So present your best aspect.

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3. Ask your guides: If you are having any difficulty with your research, then do not hesitate to share your difficulty with your guide (if you have one). They will surely help you out and resolve your doubts. If you can't clarify what exactly you require for your work, then ask your supervisor to help you with an alternative. He or she might also provide you with a list of essential readings.

4. Use of computer is recommended: As you are doing research in the field of computer science then this point is quite obvious. Use right software: Always use good quality software packages. If you are not capable of judging good software, then you can lose the quality of your paper unknowingly. There are various programs available to help you which you can get through the internet.

5. Use the internet for help: An excellent start for your paper is using Google. It is a wondrous search engine, where you can have your doubts resolved. You may also read some answers for the frequent question of how to write your research paper or find a model research paper. You can download books from the internet. If you have all the required books, place importance on reading, selecting, and analyzing the specified information. Then sketch out your research paper. Use big pictures: You may use encyclopedias like Wikipedia to get pictures with the best resolution. At Global Journals, you should strictly follow here.

6. Bookmarks are useful: When you read any book or magazine, you generally use bookmarks, right? It is a good habit which helps to not lose your continuity. You should always use bookmarks while searching on the internet also, which will make your search easier.

7. Revise what you wrote: When you write anything, always read it, summarize it, and then finalize it.

8. Make every effort: Make every effort to mention what you are going to write in your paper. That means always have a good start. Try to mention everything in the introduction—what is the need for a particular research paper. Polish your work with good writing skills and always give an evaluator what he wants. Make backups: When you are going to do any important thing like making a research paper, you should always have backup copies of it either on your computer or on paper. This protects you from losing any portion of your important data.

9. Produce good diagrams of your own: Always try to include good charts or diagrams in your paper to improve quality. Using several unnecessary diagrams will degrade the quality of your paper by creating a hodgepodge. So always try to include diagrams which were made by you to improve the readability of your paper. Use of direct quotes: When you do research relevant to literature, history, or current affairs, then use of quotes becomes essential, but if the study is relevant to science, use of quotes is not preferable.

10.Use proper verb tense: Use proper verb tenses in your paper. Use past tense to present those events that have happened. Use present tense to indicate events that are going on. Use future tense to indicate events that will happen in the future. Use of wrong tenses will confuse the evaluator. Avoid sentences that are incomplete.

11. Pick a good study spot: Always try to pick a spot for your research which is quiet. Not every spot is good for studying.

12. Know what you know: Always try to know what you know by making objectives, otherwise you will be confused and unable to achieve your target.

13. Use good grammar: Always use good grammar and words that will have a positive impact on the evaluator; use of good vocabulary does not mean using tough words which the evaluator has to find in a dictionary. Do not fragment sentences. Eliminate one-word sentences. Do not ever use a big word when a smaller one would suffice.

Verbs have to be in agreement with their subjects. In a research paper, do not start sentences with conjunctions or finish them with prepositions. When writing formally, it is advisable to never split an infinitive because someone will (wrongly) complain. Avoid clichés like a disease. Always shun irritating alliteration. Use language which is simple and straightforward. Put together a neat summary.

14. Arrangement of information: Each section of the main body should start with an opening sentence, and there should be a changeover at the end of the section. Give only valid and powerful arguments for your topic. You may also maintain your arguments with records.

15. Never start at the last minute: Always allow enough time for research work. Leaving everything to the last minute will degrade your paper and spoil your work.

16. Multitasking in research is not good: Doing several things at the same time is a bad habit in the case of research activity. Research is an area where everything has a particular time slot. Divide your research work into parts, and do a particular part in a particular time slot.

17. Never copy others' work: Never copy others' work and give it your name because if the evaluator has seen it anywhere, you will be in trouble. Take proper rest and food: No matter how many hours you spend on your research activity, if you are not taking care of your health, then all your efforts will have been in vain. For quality research, take proper rest and food.

18. Go to seminars: Attend seminars if the topic is relevant to your research area. Utilize all your resources.

19. Refresh your mind after intervals: Try to give your mind a rest by listening to soft music or sleeping in intervals. This will also improve your memory. Acquire colleagues: Always try to acquire colleagues. No matter how sharp you are, if you acquire colleagues, they can give you ideas which will be helpful to your research.

20. Think technically: Always think technically. If anything happens, search for its reasons, benefits, and demerits. Think and then print: When you go to print your paper, check that tables are not split, headings are not detached from their descriptions, and page sequence is maintained.

21. Adding unnecessary information: Do not add unnecessary information like "I have used MS Excel to draw graphs." Irrelevant and inappropriate material is superfluous. Foreign terminology and phrases are not apropos. One should never take a broad view. Analogy is like feathers on a snake. Use words properly, regardless of how others use them. Remove quotations. Puns are for kids, not grunt readers. Never oversimplify: When adding material to your research paper, never go for oversimplification; this will definitely irritate the evaluator. Be specific. Never use rhythmic redundancies. Contractions shouldn't be used in a research paper. Comparisons are as terrible as clichés. Give up ampersands, abbreviations, and so on. Remove commas that are not necessary. Parenthetical words should be between brackets or commas. Understatement is always the best way to put forward earth-shaking thoughts. Give a detailed literary review.

22. Report concluded results: Use concluded results. From raw data, filter the results, and then conclude your studies based on measurements and observations taken. An appropriate number of decimal places should be used. Parenthetical remarks are prohibited here. Proofread carefully at the final stage. At the end, give an outline to your arguments. Spot perspectives of further study of the subject. Justify your conclusion at the bottom sufficiently, which will probably include examples.

23. Upon conclusion: Once you have concluded your research, the next most important step is to present your findings. Presentation is extremely important as it is the definite medium though which your research is going to be in print for the rest of the crowd. Care should be taken to categorize your thoughts well and present them in a logical and neat manner. A good quality research paper format is essential because it serves to highlight your research paper and bring to light all necessary aspects of your research.

Informal Guidelines of Research Paper Writing

Key points to remember:

- Submit all work in its final form.
- Write your paper in the form which is presented in the guidelines using the template.
- Please note the criteria peer reviewers will use for grading the final paper.

Final points:

One purpose of organizing a research paper is to let people interpret your efforts selectively. The journal requires the following sections, submitted in the order listed, with each section starting on a new page:

The introduction: This will be compiled from reference matter and reflect the design processes or outline of basis that directed you to make a study. As you carry out the process of study, the method and process section will be constructed like that. The results segment will show related statistics in nearly sequential order and direct reviewers to similar intellectual paths throughout the data that you gathered to carry out your study.

The discussion section:

This will provide understanding of the data and projections as to the implications of the results. The use of good quality references throughout the paper will give the effort trustworthiness by representing an alertness to prior workings.

Writing a research paper is not an easy job, no matter how trouble-free the actual research or concept. Practice, excellent preparation, and controlled record-keeping are the only means to make straightforward progression.

General style:

Specific editorial column necessities for compliance of a manuscript will always take over from directions in these general guidelines.

To make a paper clear: Adhere to recommended page limits.

Mistakes to avoid:

- Insertion of a title at the foot of a page with subsequent text on the next page.
- Separating a table, chart, or figure—confine each to a single page.
- Submitting a manuscript with pages out of sequence.
- In every section of your document, use standard writing style, including articles ("a" and "the").
- Keep paying attention to the topic of the paper.
- Use paragraphs to split each significant point (excluding the abstract).
- Align the primary line of each section.
- Present your points in sound order.
- Use present tense to report well-accepted matters.
- Use past tense to describe specific results.
- Do not use familiar wording; don't address the reviewer directly. Don't use slang or superlatives.
- Avoid use of extra pictures—include only those figures essential to presenting results.

Title page:

Choose a revealing title. It should be short and include the name(s) and address(es) of all authors. It should not have acronyms or abbreviations or exceed two printed lines.

Abstract: This summary should be two hundred words or less. It should clearly and briefly explain the key findings reported in the manuscript and must have precise statistics. It should not have acronyms or abbreviations. It should be logical in itself. Do not cite references at this point.

An abstract is a brief, distinct paragraph summary of finished work or work in development. In a minute or less, a reviewer can be taught the foundation behind the study, common approaches to the problem, relevant results, and significant conclusions or new questions.

Write your summary when your paper is completed because how can you write the summary of anything which is not yet written? Wealth of terminology is very essential in abstract. Use comprehensive sentences, and do not sacrifice readability for brevity; you can maintain it succinctly by phrasing sentences so that they provide more than a lone rationale. The author can at this moment go straight to shortening the outcome. Sum up the study with the subsequent elements in any summary. Try to limit the initial two items to no more than one line each.

Reason for writing the article—theory, overall issue, purpose.

- Fundamental goal.
- To-the-point depiction of the research.
- Consequences, including definite statistics—if the consequences are quantitative in nature, account for this; results of any numerical analysis should be reported. Significant conclusions or questions that emerge from the research.

Approach:

- o Single section and succinct.
- o An outline of the job done is always written in past tense.
- o Concentrate on shortening results—limit background information to a verdict or two.
- o Exact spelling, clarity of sentences and phrases, and appropriate reporting of quantities (proper units, important statistics) are just as significant in an abstract as they are anywhere else.

Introduction:

The introduction should "introduce" the manuscript. The reviewer should be presented with sufficient background information to be capable of comprehending and calculating the purpose of your study without having to refer to other works. The basis for the study should be offered. Give the most important references, but avoid making a comprehensive appraisal of the topic. Describe the problem visibly. If the problem is not acknowledged in a logical, reasonable way, the reviewer will give no attention to your results. Speak in common terms about techniques used to explain the problem, if needed, but do not present any particulars about the protocols here.

The following approach can create a valuable beginning:

- Explain the value (significance) of the study.
- Defend the model—why did you employ this particular system or method? What is its compensation? Remark upon its appropriateness from an abstract point of view as well as pointing out sensible reasons for using it.
- Present a justification. State your particular theory(-ies) or aim(s), and describe the logic that led you to choose them.
- Briefly explain the study's tentative purpose and how it meets the declared objectives.

Approach:

Use past tense except for when referring to recognized facts. After all, the manuscript will be submitted after the entire job is done. Sort out your thoughts; manufacture one key point for every section. If you make the four points listed above, you will need at least four paragraphs. Present surrounding information only when it is necessary to support a situation. The reviewer does not desire to read everything you know about a topic. Shape the theory specifically—do not take a broad view.

As always, give awareness to spelling, simplicity, and correctness of sentences and phrases.

Procedures (methods and materials):

This part is supposed to be the easiest to carve if you have good skills. A soundly written procedures segment allows a capable scientist to replicate your results. Present precise information about your supplies. The suppliers and clarity of reagents can be helpful bits of information. Present methods in sequential order, but linked methodologies can be grouped as a segment. Be concise when relating the protocols. Attempt to give the least amount of information that would permit another capable scientist to replicate your outcome, but be cautious that vital information is integrated. The use of subheadings is suggested and ought to be synchronized with the results section.

When a technique is used that has been well-described in another section, mention the specific item describing the way, but draw the basic principle while stating the situation. The purpose is to show all particular resources and broad procedures so that another person may use some or all of the methods in one more study or referee the scientific value of your work. It is not to be a step-by-step report of the whole thing you did, nor is a methods section a set of orders.

Materials:

Materials may be reported in part of a section or else they may be recognized along with your measures.

Methods:

- Report the method and not the particulars of each process that engaged the same methodology.
- Describe the method entirely.
- To be succinct, present methods under headings dedicated to specific dealings or groups of measures.
- Simplify—detail how procedures were completed, not how they were performed on a particular day.
- If well-known procedures were used, account for the procedure by name, possibly with a reference, and that's all.

Approach:

It is embarrassing to use vigorous voice when documenting methods without using first person, which would focus the reviewer's interest on the researcher rather than the job. As a result, when writing up the methods, most authors use third person passive voice.

Use standard style in this and every other part of the paper—avoid familiar lists, and use full sentences.

What to keep away from:

- Resources and methods are not a set of information.
- Skip all descriptive information and surroundings—save it for the argument.
- Leave out information that is immaterial to a third party.

Results:

The principle of a results segment is to present and demonstrate your conclusion. Create this part as entirely objective details of the outcome, and save all understanding for the discussion.

The page length of this segment is set by the sum and types of data to be reported. Use statistics and tables, if suitable, to present consequences most efficiently.

You must clearly differentiate material which would usually be incorporated in a study editorial from any unprocessed data or additional appendix matter that would not be available. In fact, such matters should not be submitted at all except if requested by the instructor.

Content:

- Sum up your conclusions in text and demonstrate them, if suitable, with figures and tables.
- In the manuscript, explain each of your consequences, and point the reader to remarks that are most appropriate.
- Present a background, such as by describing the question that was addressed by creation of an exacting study.
- Explain results of control experiments and give remarks that are not accessible in a prescribed figure or table, if appropriate.
- Examine your data, then prepare the analyzed (transformed) data in the form of a figure (graph), table, or manuscript.

What to stay away from:

- Do not discuss or infer your outcome, report surrounding information, or try to explain anything.
- Do not include raw data or intermediate calculations in a research manuscript.
- Do not present similar data more than once.
- A manuscript should complement any figures or tables, not duplicate information.
- Never confuse figures with tables—there is a difference.

Approach:

As always, use past tense when you submit your results, and put the whole thing in a reasonable order.

Put figures and tables, appropriately numbered, in order at the end of the report.

If you desire, you may place your figures and tables properly within the text of your results section.

Figures and tables:

If you put figures and tables at the end of some details, make certain that they are visibly distinguished from any attached appendix materials, such as raw facts. Whatever the position, each table must be titled, numbered one after the other, and include a heading. All figures and tables must be divided from the text.

Discussion:

The discussion is expected to be the trickiest segment to write. A lot of papers submitted to the journal are discarded based on problems with the discussion. There is no rule for how long an argument should be.

Position your understanding of the outcome visibly to lead the reviewer through your conclusions, and then finish the paper with a summing up of the implications of the study. The purpose here is to offer an understanding of your results and support all of your conclusions, using facts from your research and generally accepted information, if suitable. The implication of results should be fully described.

Infer your data in the conversation in suitable depth. This means that when you clarify an observable fact, you must explain mechanisms that may account for the observation. If your results vary from your prospect, make clear why that may have happened. If your results agree, then explain the theory that the proof supported. It is never suitable to just state that the data approved the prospect, and let it drop at that. Make a decision as to whether each premise is supported or discarded or if you cannot make a conclusion with assurance. Do not just dismiss a study or part of a study as "uncertain."

Research papers are not acknowledged if the work is imperfect. Draw what conclusions you can based upon the results that you have, and take care of the study as a finished work.

- You may propose future guidelines, such as how an experiment might be personalized to accomplish a new idea.
- Give details of all of your remarks as much as possible, focusing on mechanisms.
- Make a decision as to whether the tentative design sufficiently addressed the theory and whether or not it was correctly restricted. Try to present substitute explanations if they are sensible alternatives.
- One piece of research will not counter an overall question, so maintain the large picture in mind. Where do you go next? The best studies unlock new avenues of study. What questions remain?
- Recommendations for detailed papers will offer supplementary suggestions.

Approach:

When you refer to information, differentiate data generated by your own studies from other available information. Present work done by specific persons (including you) in past tense.

Describe generally acknowledged facts and main beliefs in present tense.

The Administration Rules

Administration Rules to Be Strictly Followed before Submitting Your Research Paper to Global Journals Inc.

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Segment draft and final research paper: You have to strictly follow the template of a research paper, failing which your paper may get rejected. You are expected to write each part of the paper wholly on your own. The peer reviewers need to identify your own perspective of the concepts in your own terms. Please do not extract straight from any other source, and do not rephrase someone else's analysis. Do not allow anyone else to proofread your manuscript.

Written material: You may discuss this with your guides and key sources. Do not copy anyone else's paper, even if this is only imitation, otherwise it will be rejected on the grounds of plagiarism, which is illegal. Various methods to avoid plagiarism are strictly applied by us to every paper, and, if found guilty, you may be blacklisted, which could affect your career adversely. To guard yourself and others from possible illegal use, please do not permit anyone to use or even read your paper and file.

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Topics	Grades		
	A-B	**C-D**	**E-F**
Abstract	Clear and concise with appropriate content, Correct format. 200 words or below	Unclear summary and no specific data, Incorrect form Above 200 words	No specific data with ambiguous information Above 250 words
Introduction	Containing all background details with clear goal and appropriate details, flow specification, no grammar and spelling mistake, well organized sentence and paragraph, reference cited	Unclear and confusing data, appropriate format, grammar and spelling errors with unorganized matter	Out of place depth and content, hazy format
Methods and Procedures	Clear and to the point with well arranged paragraph, precision and accuracy of facts and figures, well organized subheads	Difficult to comprehend with embarrassed text, too much explanation but completed	Incorrect and unorganized structure with hazy meaning
Result	Well organized, Clear and specific, Correct units with precision, correct data, well structuring of paragraph, no grammar and spelling mistake	Complete and embarrassed text, difficult to comprehend	Irregular format with wrong facts and figures
Discussion	Well organized, meaningful specification, sound conclusion, logical and concise explanation, highly structured paragraph reference cited	Wordy, unclear conclusion, spurious	Conclusion is not cited, unorganized, difficult to comprehend
References	Complete and correct format, well organized	Beside the point, Incomplete	Wrong format and structuring

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