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Emotion Detection in Arabic Text using Machine Learning Methods

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Abstract

Emotions are essential to any or all languages and are notoriously challenging to grasp. While numerous studies discussing the recognition of emotion in English, Arabic emotion recognition research remains in its early stages. The textual data with embedded emotions has increased considerably with the Internet and social networking platforms. This study aims to tackle the challenging problem of emotion detection in Arabic text. Recent studies found that dialect diversity and morphological complexity in the Arabic language, with the limited access of annotated training datasets for Arabic emotions, pose the foremost significant challenges to Arabic emotion detection. Social media is becoming a more popular kind of communication where users can share their thoughts and express emotions like joy, sadness, anger, surprise, hate, fear, so on some range of subjects in ways they'd not typically neutralize person. Social media also present different challenges which include spelling mistakes, new slang, and incorrect use of grammar. The previous few years have seen a giant increase in interest in text emotion detection.

Index terms— emotion detection, machine learning, arabic text, KNN, DT, SVM, naive bayes.

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ifferent challenges which include spelling mistakes, new slang, and incorrect use of grammar. The previous few years have seen a giant increase in interest in text emotion detection The study of Arabic emotions might be a results of the Arab world's considerable influence on global politics and thus the economy. There are numerous uses for the automated recognition of emotions within the textual content on Facebook and Twitter, including company development, program design, content response. in line with recent studies, it's possible to identify emotions in emotion detection, machine learning, arabic text, KNN, DT, SVM, naive bayes 170203

1 Learning Methods

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Attribution-NonCommercial-ND 4.0). You must give appropriate credit to authors and reference this article if parts of the article are reproduced in any manner. Applicable licensing terms are at <https://creativecommons.org/licenses/by-nc-Global Journal of Computer Science and Technology: G Emotions> are essential to any or all languages and are notoriously challenging to grasp. While numerous studies discussing

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56 Emotion Detection in Arabic Text using Machine Learning Methods

57 3 By Fatimah Khalil Aljwari

58 University of Jeddah Introduction currently, social media plays a necessary role in way of life and practice.
59 immeasurable individuals use social media for various purposes. Every second, a major amount of knowledge
60 flow via online networks, containing valuable information that may be extracted if the information are correctly
61 processed and analyzed [8]. Social networking media became essential for expressing emotions to the planet
62 due to the fast growth of the web. Several individuals use textual content, audio, video, and images to express
63 their emotions or perceptions [9]. The Affective Computing research field has been an energetic research domain
64 and recently gained great popularity. It aims at providing machines with a human-like ability to grasp and
65 answer human emotions, with more natural interaction between humans and machines [10]. Emotions are a vital
66 component of human life. Emotions affect human decision-making and can enable us to speak with the planet in a
67 very better way. Emotion detection, also called emotion recognition, identifies an individual's feelings or emotions,
68 for instance, joy, sadness, or fury [9]. "Emotion detection," "emotion analysis," and "emotion identification" are
69 all expressions that are periodically used interchangeably. The sentiment analysis could be a means of evaluating
70 if data is negative, positive, or neutral. In contrast, emotion recognition specifies different human emotion types,
71 like joy, love, sadness, happiness, anger, and surprise [9]. quite 400 million people speak Arabic, the official
72 language of twenty-two countries. It is the Internet's fourth most generally used language [10]. Languages
73 utilized in social media, such as Twitter, differ wildly from that utilized on other platforms, like Wikipedia.
74 The English language has been highly determined within the emotion detection field, including datasets and
75 dictionary availability, in contrast to the Arabic, which has minimal resources [11]. Emotion analysis has different
76 applications in every aspect of our existence, including making efficient e-learning frameworks in step with the
77 emotion of scholars, enhancing human-computer interactions, observing the mental state of people, enhancing
78 business strategies supported customer emotions, analyzing public feelings on any national, international, or the
79 political event, identifying potential criminals by analyzing the emotions of individuals after an attack or crime,
80 and improving the performance of chatbots and other automatic feedback frameworks [4]. In Additionally, text
81 emotion analysis has been a promising research topic. Analyzing the texts and identifying emotion from the words
82 and semantics could be a difficult challenge. The paper aims to automatic recognition of emotions in texts written
83 in the Arabic language by employing a model for Emotion Classification (EC) into emotion classes: Sadness,
84 joy, fear, and anger with the algorithms of machine learning. This approach utilized the SemEval-2018 Task1
85 reference dataset and focused on four emotion classes (Joy, Sad, Angry, and fear). Five forms of algorithms are
86 used supported the machine learning approach, namely K-Nearest Neighbor (KNN), Decision Tree (DT), Support
87 Vector Machine (SVM), Naive Bayes (NB), and Multinomial (NB). KNN, DT, SVM, NB, and Multinomial NB
88 classifiers are utilized in the classification process since they offer the foremost satisfactory and better accuracy
89 results among all other classifiers. The findings showed that the choice Tree and K-Nearest Neighbor classifiers
90 have the best accomplishment regarding accuracy, 0.74, While the NB and Multinomial NB classifiers acquired
91 0.69, and also the SVM obtained 0.63. The structure of this study continues to section II, which presents Problem
92 Definition and Algorithm while section III offers the recent related work on Arabic emotion recognition. Section
93 IV describes the Methodology and results of emotion analysis from Arabic texts and discusses the results. Section
94 V provides the conclusion and future work.

95 4 II.

96 5 Problem Definition and Algorithm

97 This section briefly presents the Problem Definition and Algorithm for the detection of emotion in texts written
98 in the Arabic language.

99 **6 a) Problem Definition**

100 Most research papers in this field focus on negative or positive emotion analysis and do not go deeply into
101 emotion analysis, especially in Arabic. Research in emotion analysis for Arabic has been minimal compared to
102 other languages like English. This paper addresses the emotion detection problem in Arabic tweets and presents
103 a model to categorize emotions into sadness, joy, anger, and fear. Furthermore, the current work can provide
104 many benefits for governments, health authorities, and decision-makers to monitor people's emotions on social
105 media content. Additionally, it can improve business strategies according to customers' emotions and recognize
106 potential criminals when analyzing people's emotions after an attack or crime.

107 **7 b) Algorithm Definition**

108 The Machine Learning approach learns from the info and tries to hunt out the relation between a given input
109 text and also the corresponding output emotion by building a prediction model. This approach is split into two
110 categories:

111 **8 i. Supervised learning approach**

112 Based on a labeled or annotated dataset, the supervised approach takes a component of this data for the training
113 process using an emotion classifier. This trained data is then examined, and a model is made. The remaining
114 data within the dataset is classed supported this previously trained classifier into the emotion category.

115 **9 ii. Unsupervised learning approach**

116 The unsupervised approach relies on a nonlabeled dataset. The approach inherent the drawbacks of the ML
117 algorithm. It requires an oversized dataset for the training process to be accurate. The Machine Learning
118 approach solves the emotion detection issue by categorizing texts into various emotion classifications using the
119 mentioned algorithms. This process is usually done employing a supervised or unsupervised ML technique. To
120 categorize the tweet into each categorization (anger, joy, sadness, and fear), we applied five different supervised
121 machine-learning approaches: KNN, DT, SVM, NB, and NB. Following could even be an inventory of the
122 classifiers discussed during this work:a. K-Nearest Neighbor (KNN)

123 KNN is addition-ally a fairly AI supported machine learning algorithms in classification, processing, statistical
124 pattern recognition, and much of more. This method in our experiment can classify an emotion correctly [15].
125 KNN classifies a replacement instance within the test set supported the shortest distance between it and numeric
126 neighbors (k) stored within the training set using the Euclidian Distance equation [13].

127 **10 b. Decision Tree (DT)**

128 A Decision Tree could even be a mode of a tree structure utilized in classification and regression models. It breaks
129 down the datasets into smaller subsets and incrementally develops them into nodes and leaves. The branches
130 of the selection tree represent the category of the datasets. the selection tree is split into four emotion classes:
131 joy, sadness, anger, and fear. The selection tree's goal is to substantiate it achieves maximum separation among
132 classes at each level.

133 **11 c. Support Vector Machine (SVM)**

134 SVM could even be a supervised ML algorithm. The model is straightforward, and far of individuals value more
135 highly to use this model thanks to its less computational power and it gives significant accuracy. SVM conducts
136 linear classification and performs nonlinear classification alright [6]. This model's idea is straightforward: The
137 algorithm plots each data item as some extent in n-dimensional space representing the number of features. Then,
138 it'll use hyper-plane to differentiate between features and classes of emotion.

139 **12 d. NB**

140 NB includes several algorithms of classification based on the Bayes Theorem. The NB classifier presents significant
141 results when it is used for text analyzing data. Such an algorithm offers a prospect examining the study's dataset
142 [12].

143 **13 e. Multinomial (NB)**

144 Multinomial NB classifier works on the concept of term frequency, which suggests what percentage times the
145 word occurs during an extremely document. MNB is specially designed for text data and a particular version of
146 Naive Bayes [6]. MNB tells two facts about whether the word appears during a very document and its frequency
147 there in document.

14 III.

15 Literature Review

Although there are many studies during this domain, one amongst the tough challenges for all researchers during this domain is to use emotion analysis and classification for Arabic tweets, which remains limited, most Arabic studies specialise in sentiment analysis to classify tweets into positive/negative classes, underestimating the utilization of emotion detection and analysis to draw down different emotions. The literature review presents the foremost recent works on emotion detection in languages.

Mansy, A et al. [1] researchers proposed an ensemble deep learning approach to research Emotion from user text in Arabic Tweets. They evaluated using the SemEval-2018-Task1-dataset published in a very multilabel classification task. The proposed model was supported three deep learning models. Two models are particular styles of Recurrent Neural Networks (RNNs), the Bidirectional Gated Recurrent Unit (Bi-GRU) and Bidirectional Long Short Term Memory Model (Bi-LSTM). The third may be a pretrained model (PLM) supported Bidirectional Encoder Representations from Transformers (BERT) NAMED MARBERT. The results of the proposed ensemble model showed outperformance over the individual models (Bi-LSTM, Bi-GRU, and MARBERT). They showed an accuracy of 0.54, precision of 0.63, 0.55 in an exceedingly recall, 0.70 in Macro F1 Score, and 0.52 in micro F1 Score.

In addition, Khalil et al. [2] proposed a Bi-LSTM deep learning model for EC in tweets written in Arabic that were employed in the SemEval-2018 dataset. The Aravec with CBOW for the word embedding phase has been employed in feature extraction. Their results have shown an Accuracy of 0.498, and a Micro F1 score of 0.615.

Another study on Arabic emotion analysis was proposed in [3]. The authors addressed the emotion detection problem in Arabic tweets. A tweet may have multiple emotional states (for example, joy, love, and optimism). during this case, the emotional classification of tweets is framed as a multilabel classification problem. The proposed approach combined the transformer-based Arabic (AraBERT) model and an attention-based LSTM-BiLSTM deep model. The approach used a publicly available benchmark dataset of SemEval-2018 Task 1, where the dataset is formed for multilabel detection of emotion in these tweets. The findings show that such an approach presents accuracy of nearly 54.

A multilabel classification was employed to detect emotions in Arabic tweets by [4] For instance, AlZoubi et al. [5] have implemented an ensemble approach that contains Conventional Neural Networks (CNN), Bidirectional GRU-CNN (BiGRU-CNN), and XGBoost regressor (XGB) to be utilized in solving the EC of the SemEval-2018 dataset written within the Semitic. The ensemble approach used TF-IDF, wordlevel embedding, and lexicon features. Results show that their model achieved a precision of 69. In addition, Hussein, et al. [6] followed the machine learning method to detect emotion in Text Mining Data supported Arabic Text. They collected text mining data from the internet while focusing on four emotion classes (sad, happy, afraid, and angry). Three sorts of techniques are used supported machine learning approaches include KNN, NB, and SVM algorithm. The findings also showed that NB had the best accomplishment regarding accuracy. NB classifiers achieved 70, comparing to SVM that obtained 68.33, while KNN yielded 51.67. Saad et al. [7] proposed a similar model to categorize emotions from the Malay language. The dataset used consists of Malay children's short stories. over 200 short stories were collected, each story varying from 20-50 words. The TF-IDF is extracted from the text and classified using SVM and DT. Four common emotions, happy, angry, fearful, and sad, are classified using the 2 classifiers. Results showed that the choice Tree outperformed the SVM by a 22.2 accuracy rate.

16 Experimental Evaluation

This section discusses the used dataset and the method-ologies to identify emotions of tweets written in Arabic by utilizing (5) algorithms of machine learning: KNN, DT, SVM, NB, and Multinomial NB. The final section highlights the outcomes of this process.

The main phases of the methodology are shown in Fig. ???. The methodology consisted of the dataset, preprocessing, features engineering, supervised machine learning, and classified emotions based on four emotions (anger, joy, sadness, and fear).

17 a) Dataset

This section discusses the used dataset in which the experiments are performed using the reference emotion detection SemEval-2018 (Affect in Tweets) dataset. The dataset is the public benchmark dataset created for the detection of emotions in tweets written in Arabic. Each tweet is labeled as one of the emotions (joy, anger, sadness, and fear.). All these tweets are in Arabic text. We used only the ELoc for our experiment with four basic emotion categories. The training dataset trains the classifier and the test dataset examines the structured model to show identify the value of trained model.

18 b) Preprocessing

Data preprocessing is taken into account one among the essential phases in machine learning to avoid misleading results and obtain better insights. during this section, the preprocessing steps are discussed as follow: The tweet from the SemEval2018 dataset has been preprocessed using the foremost common preprocessing techniques, like

206 removing stop words, repeating chars, English characters, mentions, punctuation marks, and Arabic diacritics.
207 Also, text normalization has been added.

208 ? English Characters Removal: during this step, all English characters in both lower and upper cases (A-Z, a-z)
209 are removed. ? TF-IDF TF-IDF is one in every of the foremost used text feature extraction techniques because
210 it provides helpful insight into the essential features of text documents. during this paper, TF IDF is chosen
211 because the feature extraction technique. It computes the merchandise of the 2 statistics: TF-IDF describes
212 how the word is important to a tweet in an exceedingly collection of tweets. the worth of TF-IDF increases
213 correspondingly to the quantity of times a word appears within the tweets. The more a term occurs in tweets
214 belonging to some category, the more it's relative there to category. TF-IDF's function is more developed and
215 offers ideal outcomes as it can identify an emotional Arabic term. Figure (5) highlights the characters' number
216 in tweets.

217 19 d) Experiment

218 The experiment describes the approach to predicting users' emotions from their tweets. To categorize the tweet
219 into (anger, joy, sadness, and fear), we apply different machine-learning approaches: K-Nearest Neighbor, Decision
220 Tree, Support Vec-tor Machine, Naive Bayes, and Multinomial Naive Bayes. This work has been implemented on
221 a cloud-based environment, "Google Colab," owned by Google. The experiment's first and most essential phase
222 is preprocessing the tweets for training and test sets. mostly, Arabic text needs more preprocessing because of
223 its nature and structure. Therefore, the preprocessing techniques for every tweet are performed for the training
224 and testing phases. We used the dataset of the Arabic tweets presented by Semi-Eval 2018. Then classified,
225 each tweet was placed into one in all four categorizations, given an emotion and a tweet. This dataset includes
226 (934) tweets for the provided emotions: Fear, anger, sadness, and joy. The TF-IDF is extracted from the text
227 and classified using KNN, SVM, DT, NB, and Multinomial NB. We randomly split our dataset into testing and
228 training with 20-80 ratios. the proportion of every class within the dataset is shown in Fig. ???. We used the
229 training datasets to point the classifiers. In contrast, (unseen to the model), the test dataset was reserved for
230 examining the structured model to identify the suitability of the trained model. After splitting our dataset into
231 the testing and training process, 747 samples are within the training dataset and 187 within the testing dataset.
232 The results of 5 machine learning models are compared within the result section.

233 20 Evaluation Metrics

234 We use precision, accuracy recall, and F-score accuracy, in this study, to measure the EC's performance. Precision,
235 also named positive predictive value, is the documents' number labeled correctly as belonging to the positive class.
236 Sensitivity, or recall, is the documents' number that is not labeled as belonging to the positive class. Another
237 measurement that combines recall and precision is F-score. The F-score indicates how accurate the classifier
238 is (how many instances are correctly classified) and its robustness (it does not miss many instances). The last
239 measure is accuracy, which indicates the suitability of a given classifier [13]. Calculations of the measurements
240 are given in Fig. ??.

241 21 VI.

242 22 Results and Discussion

243 This section reports the performance results and discusses the model. We trained the model on the training
244 dataset for the SemEval-2018 dataset, and reported on the model performance on the test dataset. The Decision
245 Tree and K-Nearest Neighbor classifier's accuracy was 0.74, the NB and Multinomial NB classifiers obtained 0.69,
246 and the SVM 0.63. The results could be more encouraging regarding accuracy. Fig. ?? displays the accuracy
247 comparison of various machine learning models.

248 23 Conclusion

249 EC is a text categorization approach that aims to identify human feelings conveyed through texts. In recent years,
250 Arab users have expressed their emotions on many of the issues raised through the Twitter platform. Therefore,
251 this paper focused on the common classification algorithms such as DT, KNN, SVM, NB, and Multinomial (NB)
252 and applied them to a tweet's dataset as short text content. This study presented the approach for categorizing
253 the emotions of tweets written in Arabic while utilizing the machine learning model. We used the dataset of
254 Arabic tweets presented by SemEval-2018 for EI-oc task. This process used (4) emotion categories: Anger, joy,
255 fear, and sadness. The approach achieved acceptable results with 0.74 for each of the KNN and DT, while the
256 NB and Multinomial NB acquired 0.69; finally, the SVM achieved 0.63. Therefore, future research, including
257 deep learning, is promising, primarily if provided with a large, good, annotated dataset. Also, future research
258 on constructing and finding an Arabic dataset that is labeled correctly will aid and increase the advancements
259 in textual emotion detection, because it will offer a dataset that can be utilized to compare various suggested
260 investigations.

24 VIII.

25 Future Work

263 The authors intend to examine this model on bigger datasets, assess the outcomes, and employ a hybrid approach
 264 that depends on deep learning and machine learning to classify emotions in texts written in Arabic and compare
 multiple methodologies. ^{1 2}

Ref no.	Authors\Year	language	Approach	Detection method	Emotion model	Features	Dataset	Evaluation metric and Results
[1]	Mansy, A et al.,2022	Arabic	Deep Learning approach	Bi-LSTM, Bi-GRU, and MARBERT	Arabic Multilabel Emotions Classification	Word Embedding features	SemEval -2018-Task1-Ar-Ec dataset	Accuracy: 0.540 Macro F1 Score: 0.701 Precision: 0.634 Recall: 0.550 Micro F1 Score: 0.527
[2]	Khalil, E. A. H et al.,2021	Arabic	Deep Learning approach	BiLSTM	Multilabel Arabic Emotions Classification model	Word Embedding features	SemEval -2018-Task1 dataset	Validation accuracy=0.575%
[3]	Elfaik et al.,2021	Arabic	Deep Learning approach	LSTM-BiLSTM	Anger,anticipation, disgust, fear, joy, love, optimism, pessimism, sadness, surprise, and trust	Embedding features	SemEval -2018 dataset	Accuracy =(53.82%)
[4]	Alswaidan el al.,2020	Arabic	Hybrid approach	Deep feature based(DF)model and Human engineered feature based(HEF)model	Plutchik's model+love,optimism, and pessimism emotions	Stylistic,lexical, syntactic, and semantic features.	SemEval -2018 dataset	Accuracy, HEF 44.8% DF 50.5% Hybrid(HEF+DF) 51.20%
[5]	AlZoubi et al., 2020	Arabic	Ensemble and Deep learning approach	Bidirectional GRU_CNN, conventional neural networks,and XGBoost regressor	Anger, fear joy,and sadness	TF-IDF, word-level embedding, and lexicon features	SemEval -2018 dataset	Precision , Ensemble=(69%)
[6]	Hussein, A et al., 2020	Arabic	Machine learning approach	Naïve Bays, k-Nearest Neighbors (KNN), and Support Vector Machine (SVM).	Happy, Sad, Angry, fear	Word Embedding, TF-IDF features	Text Mining Data	Accuracy, NB =70%, SVM =68.33%, KNN=51.67%
[7]	Saad, M. M et al.,2018	Malay language	Machine learning approach	Support Vector Machine (SVM) and Decision Tree (DT)	Four types of emotions Happy, angry, fearful) and sad)	Term Frequency-Inverse Document Frequency (TF-IDF)	200 Malay children short stories datasets	Accuracy, SVM=30.0%, DT=62.5%

Figure 1:

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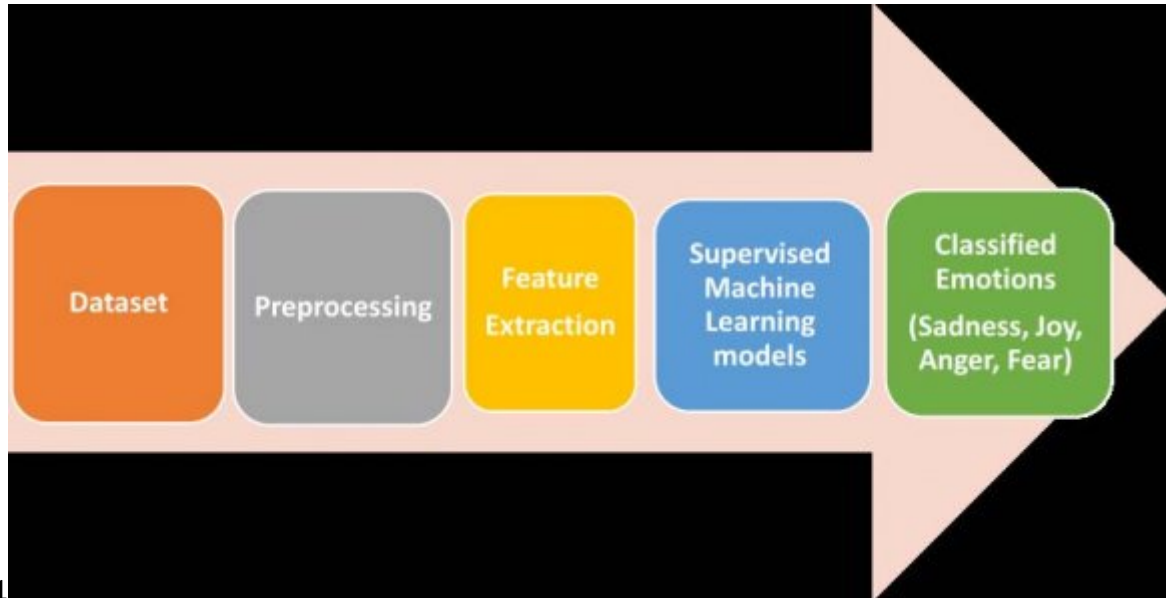


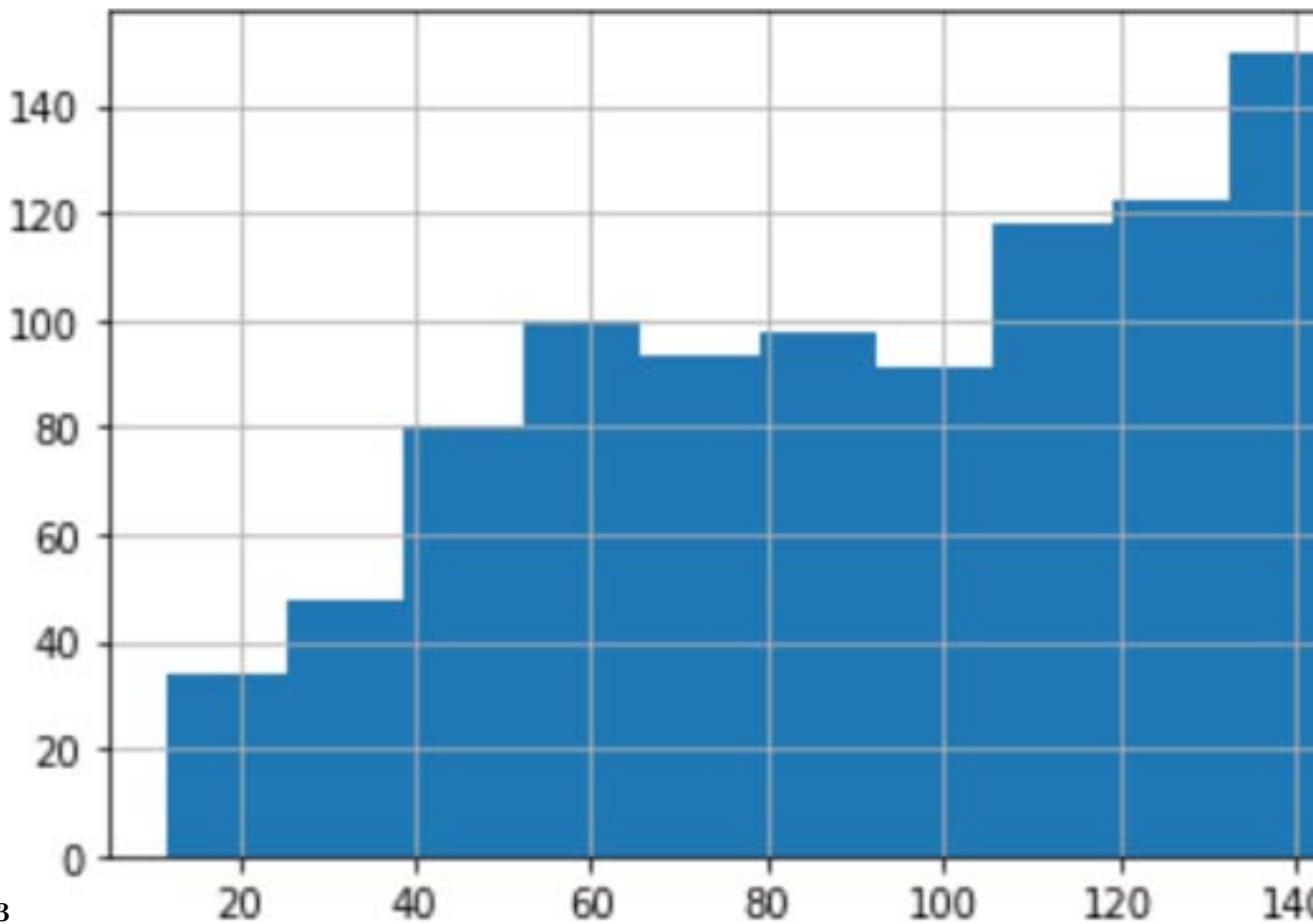
Figure 2: Fig. 1 :

ID	Tweet	Affect Dimension	Intensity Class
1	2018-Ar-00759 @mnwry1 لا ما يحتاج أعلّيج هنا ! أنتي ساقلمه ! ش	anger	3: high amount of anger can be inferred
3	2018-Ar-03121 ... فعل #طاطر من خدر وخيانة نكرنا بلعل صدام الأسود	anger	3: high amount of anger can be inferred
10	2018-Ar-04092 ... فيصل قاسم وقناه الجزيره سبب خراب سوريا ربنا بين	anger	3: high amount of anger can be inferred
17	2018-Ar-03289 @AI3mriRami @HolyIviuss كل مالي الأمر أني غاضب	anger	3: high amount of anger can be inferred
28	2018-Ar-02472 @mm_888s ... انا ضد هذا الكلام كل واحد ظروفه ليش	anger	3: high amount of anger can be inferred
...
854	2018-Ar-03946 ... القلب ما يسكنه غير الهم وروح و بكى #الهم من ا	sadness	3: high amount of sadness can be inferred
856	2018-Ar-03206 ... انا انسان #صانع هنا أتحدث عن أوجاعي وربما سأبّح	sadness	3: high amount of sadness can be inferred
865	2018-Ar-00640 ... لوحتل أنواع #الارعل لك تكرون زعلان علي #بنفسك	sadness	3: high amount of sadness can be inferred
886	2018-Ar-02781 ... بقلبي الحنين ليك حتى تعجز عيوني ذرف آخر دموع	sadness	3: high amount of sadness can be inferred
888	2018-Ar-01328 ... الروح الحقيقي هو الذي يفنصك من صوتك من غصّة الو	sadness	3: high amount of sadness can be inferred

Figure 3: Fig 1 Fig. 2 :

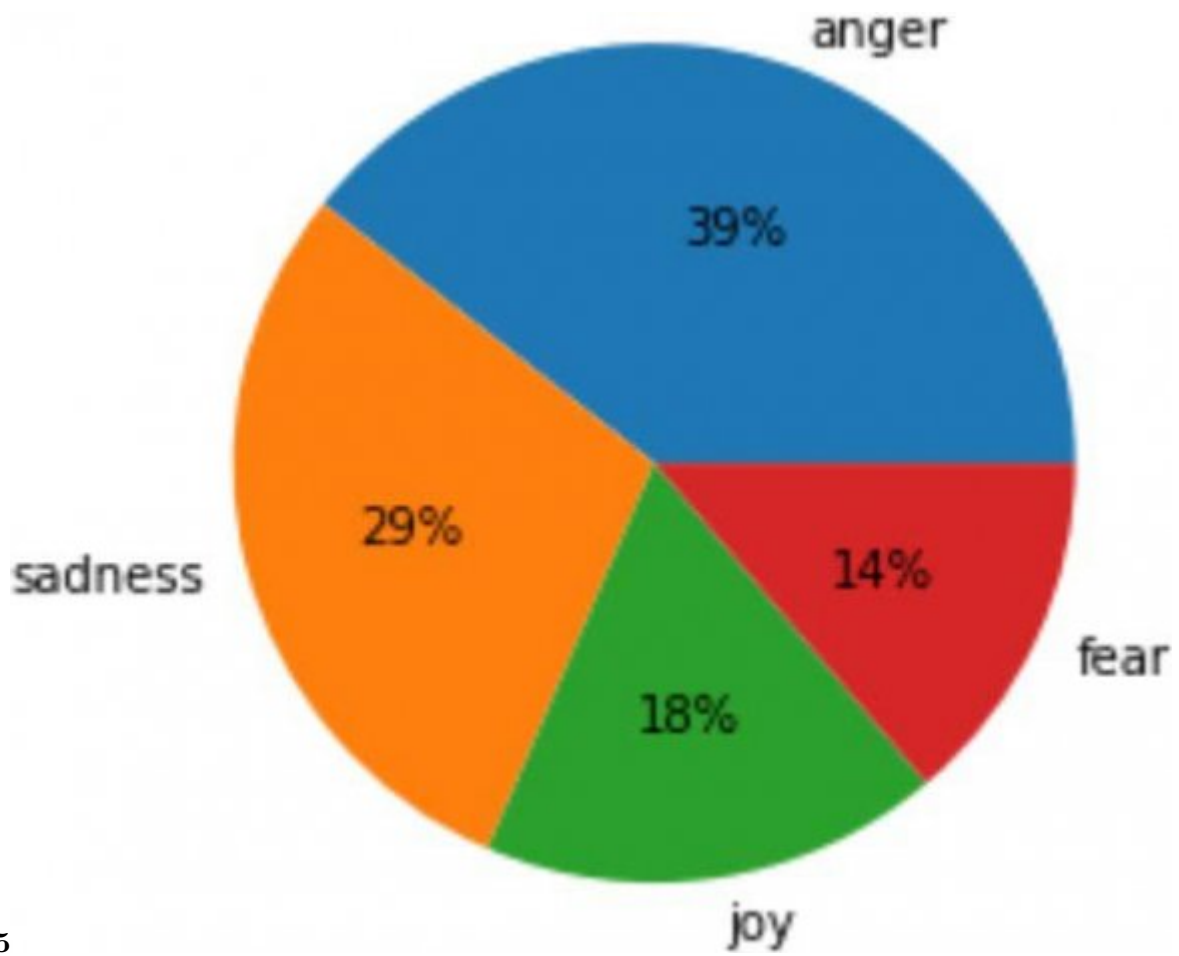
ID	Tweet	Affect Dimension	Intensity Class
5	2018-Ar-01214 ... زوحي غيرة حفاظتلك ي مجرمه اتفوه عطيك عميله وسخ	anger	3: high amount of anger can be inferred
7	2018-Ar-01154 ... فليتقوا غضب الحليم اذا غضب	anger	3: high amount of anger can be inferred
15	2018-Ar-04217 ... والله انها بصمت عار علي جبين الامه العربيه الذ	anger	3: high amount of anger can be inferred
16	2018-Ar-03520 ... امي: مخالف-ان اخوي: *بصرخ علي امي بسبها يزفها	anger	3: high amount of anger can be inferred
19	2018-Ar-03153 ... يشووش علي ايش الخيانة عياده ايران خيانة الجار	anger	3: high amount of anger can be inferred
...
333	2018-Ar-04365 ... شعور حزين : اذا كنت تضطك وفجاء تتذكر و تسكت -	sadness	3: high amount of sadness can be inferred
353	2018-Ar-01900 ... ان قلبي ليتمزق تمزقا متى تتكرت أن عيني لا تمك	sadness	3: high amount of sadness can be inferred
361	2018-Ar-01312 ... ومن #خيبة الn والكلامn من كثر المعاتبnاتبع	sadness	3: high amount of sadness can be inferred
365	2018-Ar-04247 ... انا حزين و ما أخفي عليك حزني وأنت داري ان غياب	sadness	3: high amount of sadness can be inferred
366	2018-Ar-01398 ... ياقلبي المسكين لاأحد يحس بغمرة وجعلك النفين جمر	sadness	3: high amount of sadness can be inferred

Figure 4: Fig. 3 :Fig. 4 :



3

Figure 5: Figure (3)



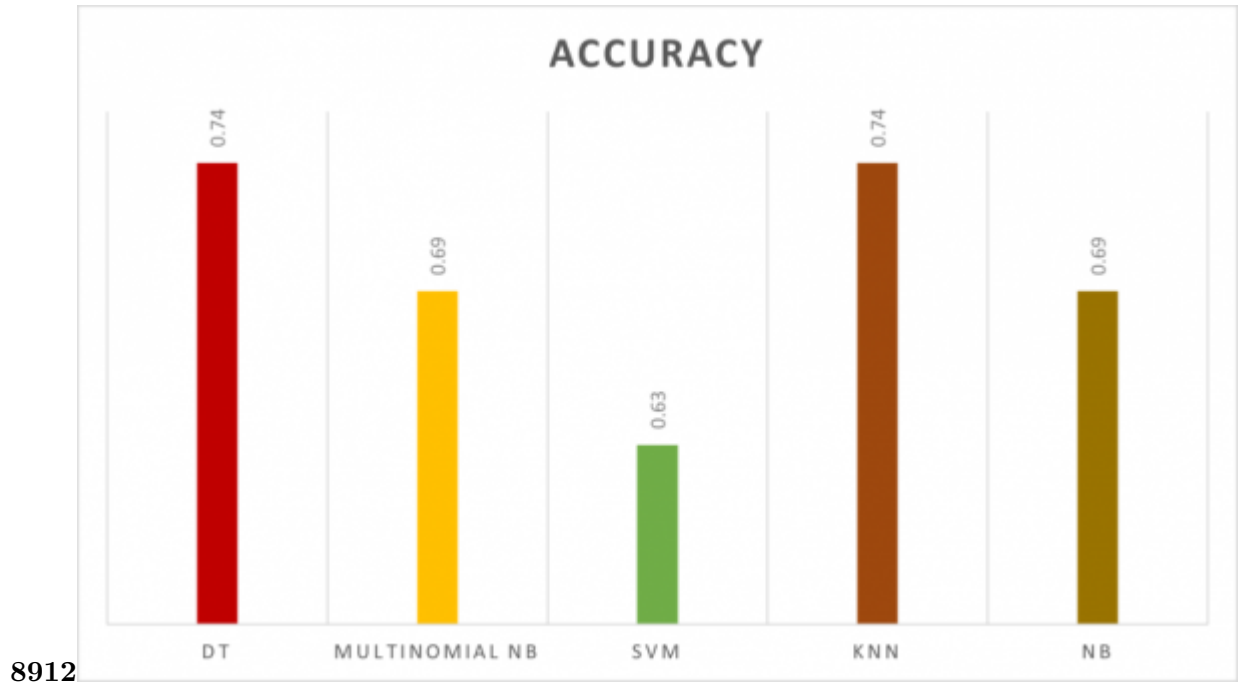
5

Figure 6: Fig. 5 :

Accuracy	$\frac{\text{True Positive} + \text{True negative}}{\text{True Positive} + \text{True negative} + \text{False Positive} + \text{False negative}}$
Recall	$\frac{\text{True Positive}}{\text{True Positive} + \text{False negative}}$
Precision	$\frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$
F-measure	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

67

Figure 7: Fig. 6 :Fig. 7 :



8912

Figure 8: Fig. 8 :Fig. 9 :Fig. 12 :

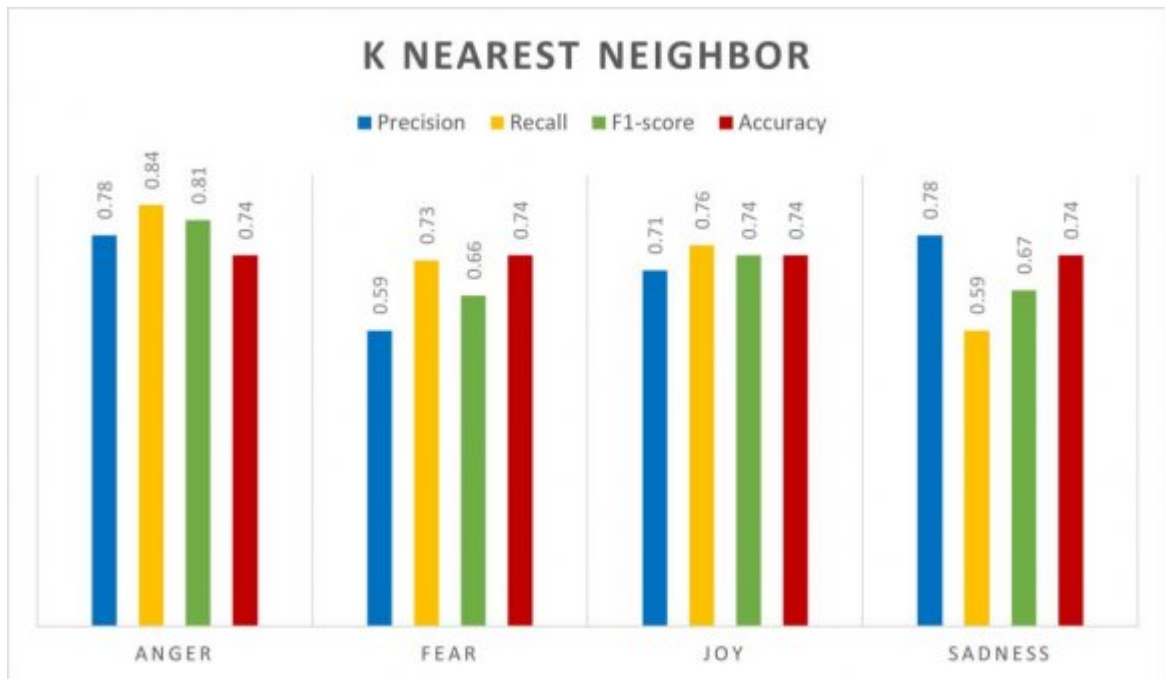


Figure 9:

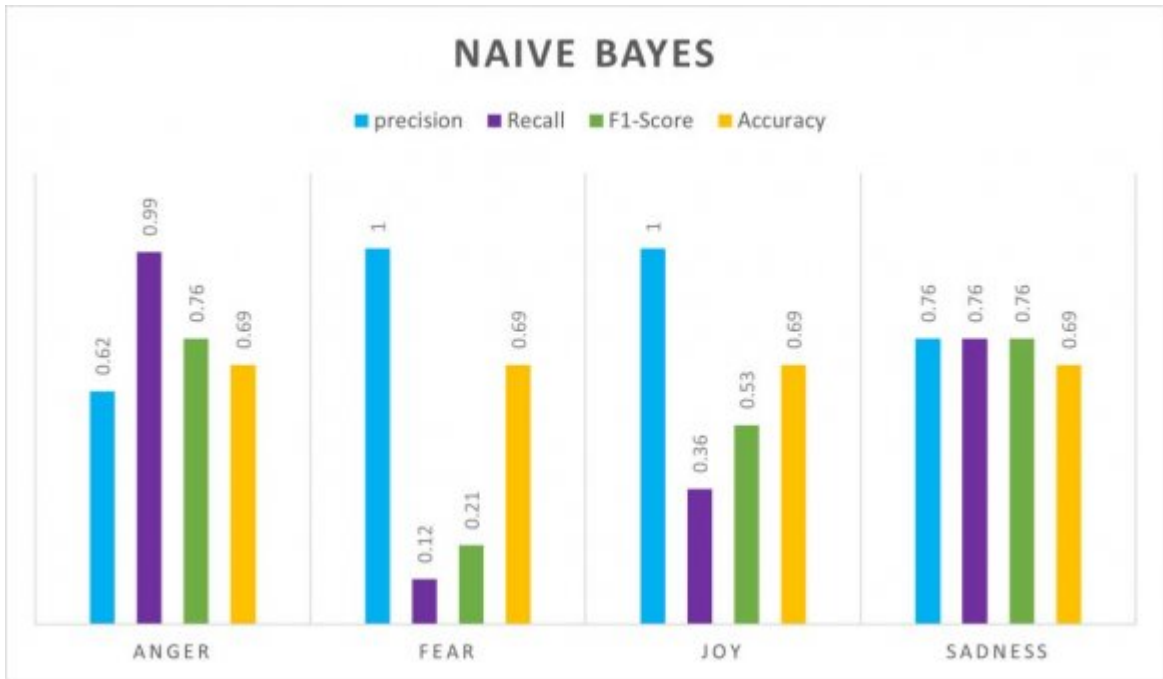


Figure 10:

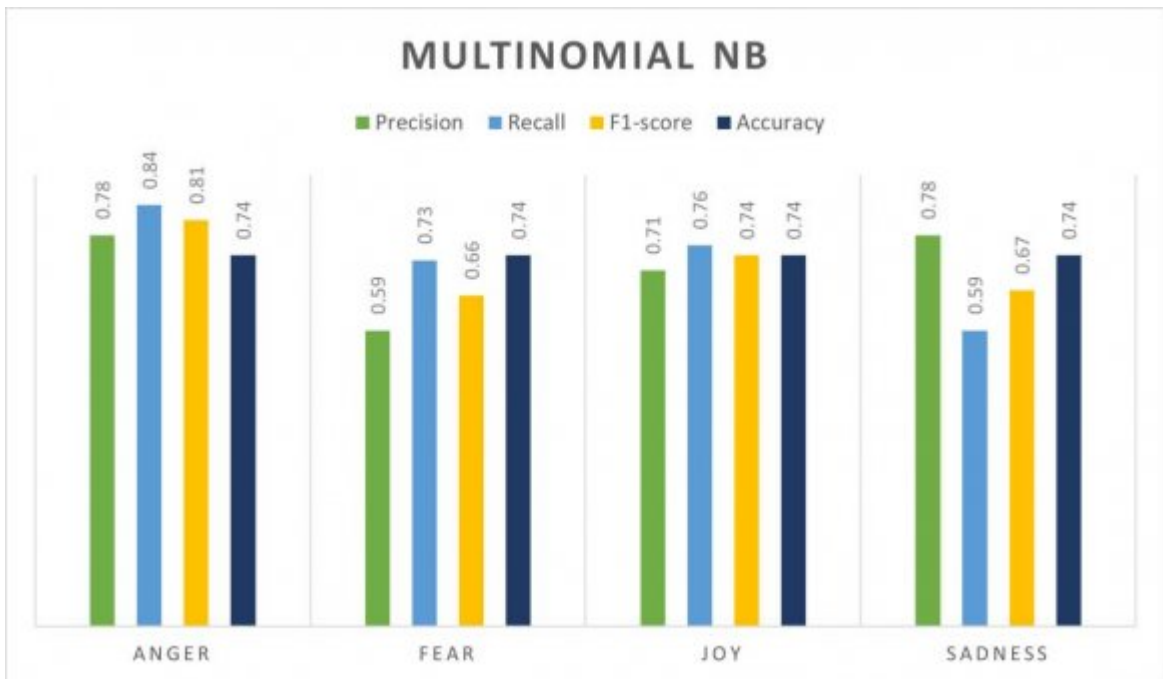


Figure 11:



Figure 12:

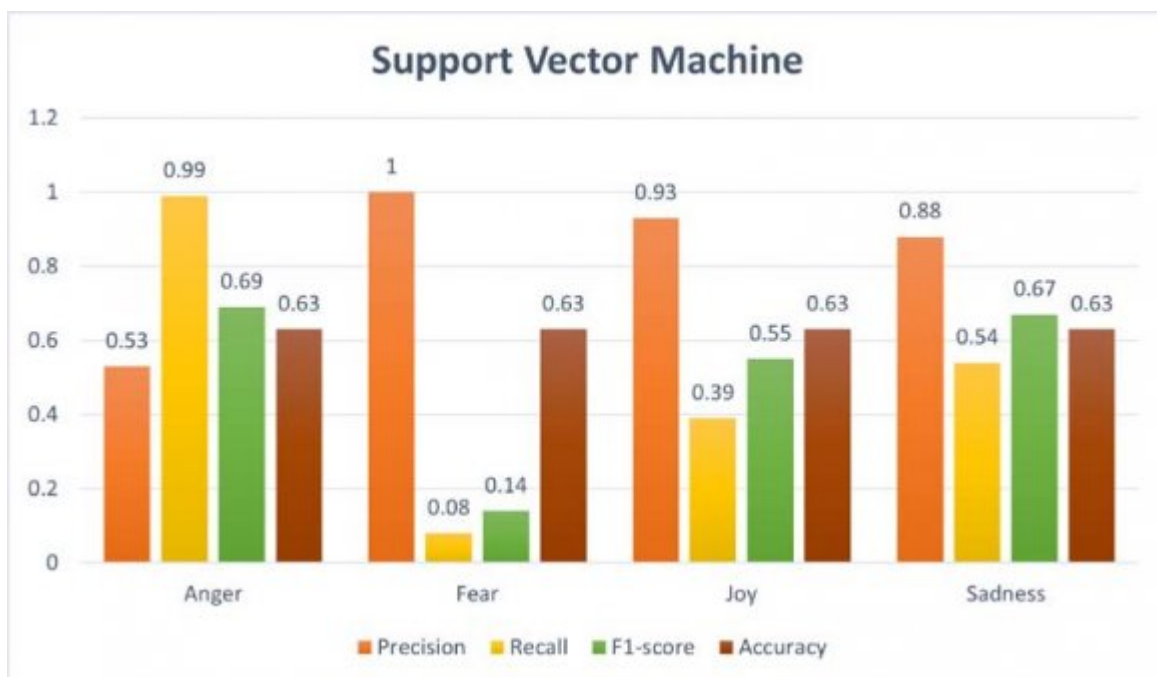


Figure 13:

-
- ? Arabic Normalization: Returning chars to their original.
 - ? Arabic Diacritics Removal: Removing all diacritics like [Fatha, Tanwin Fath, Damma, Tanwin Damm, Kasra, Tanwin Kasr, Sukun] .
 - ? Mentions Removal: Removing any mentions like @ from the tweet.
 - ? Repeated Chars Removal: Any repeating characters are removed during this step.
 - ? Punctuations Removal: Removing all punctuation marks like /:”’, +!-. . . ””-

c) Features Extraction

Feature extraction techniques aim to represent the text’s emotional value which is able to help classify the emotions into the right category. Feature extraction is essential before EC from the documents, which can be found in method such as Term Frequency-Inverse Document Frequency (TF-IDF). The next section describes the feature extraction method utilized in our proposed approach:

Figure 14:

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