

A Proposed Method to Identify the Occurrence of Diabetes in Human Body using Machine Learning Technique

Tanvir Rahman

Received: 7 September 2021 Accepted: 1 October 2021 Published: 15 October 2021

Abstract

Advanced machine-learning techniques are often used for reasoning-based diagnosis and advanced prediction system within the healthcare industry. The methods and algorithms are based on the historical clinical data and factbased Medicare evaluation. Diabetes is a global problem. Each year people are developing diabetes and due to diabetes, a lot of people are going for organ amputation. According to the World Health Organization (WHO), there is a sharp rise in number of people developing diabetes. In 1980, it was estimated that 180 million people with diabetes worldwide. This number has risen from 108 million to 422 million in 2014. WHO also reported that 1.6 million deaths in 2016 due to diabetes. Diabetes occurs due to insufficient production of insulin from pancreas. Several research show that unhealthy diet, smoking, less exercise, Body Mass Index (BMI) are the primary cause of diabetes. This paper shows the use of machine learning that can identify a patient of being diabetic or non-diabetic based on previous clinical data. In this article, a method is shown to analyze and compare the relationship between different clinical parameters such as age, BMI, Diet-chart, systolic Blood Pressure etc. After evaluating all the factors this research work successfully combined all the related factors in a single mathematical equation which is very effective to analyze the risk percentage and risk evaluation based on given input parameters by the participants or users.

Index terms—

1 Introduction a) Background

Generally, Diabetes Mellitus (DM) develops in the body silently when there are higher or uncontrolled blood glucose level exists in the blood-plasma cell for a long time. Food is the prime source of calorie and food is prime the energy generator of the body. Generally, the foods are taken in regular basic contain a lot of glucose or glucose substance. Glucose is the primary and basic unit of energy circulation and energy regulation. Glucose is divided into several substances and then the small cell units are oxidized with the sufficient amount of oxygen. Then, the small subsequent oxygen particles are transmitted through blood circulation and produce sufficient amount of energy and nutrition for all the organs of the body. Insulin is a pancreas produced Hormone which is the key component to synthesis Glucose and divide Glucose into millions of active particles. For a healthy and active person sufficient amount of Insulin is produced and emitted from Pancreas. That is why for a general Non-diabetic patient, Insulin production rate is equal to the glucose Intake of the body. So, For a Non diabetic-patient the all the amount glucose casted from daily food intake, is sufficiently divided into molecules and produces energy and rest of the unused energy is stored as Fat in the body. In the common scenario, no extra glucose particles are available in the blood plasma. According to several health study, a person is considered to be a Type-1 diabetic patient when his/her pancreas fails to generate sufficient amount of insulin to react with glucose.

The normal range of glucose level is reference value is 3.9 to 5.4 mmol/l (70 to 99 mg/dl) [1] for normal patients at fasting phase and according to American Diabetes Association the reference value at fasting time in the period of Diagnosis of diabetes is considered as 7.0 mmol/l (126 mg/dl) or above [1] and the reference value for non-diabetic patients is under 7.8 mmol/L and preferred value for Type-2 diabetes is under 8.5 mmol/L at Random diabetes testing phase (1.5 hour after food) [1][2] [5].

3 B) PROBLEM DEFINITION

45 Scientists have found a significant link between This high blood sugar and several other diseases like
46 catastrophic damage of several nerves, kidney and Renal failure, heart and vein damages, eye-sight. An
47 uncontrolled diabetes level for a long time period can also lead a patient to dead. The growth rate of diabetes
48 patients is enormous around the globe. From a report published in 2013, the International Diabetes Federation
49 (IDF) predicted the probable diabetes patients around the world. It claimed that estimated about 382 million or
50 more people worldwide are carrying excessive amount of glucose in blood and probably had been suffered from
51 diabetes, and the report also predicted that within the year of 2035, it enormous number of diabetes patients
52 can even exceed to 592 million. From the report of various health surveys it is estimated about the consequent
53 percentage of total 8.5% of the population of South-east Asian region have diabetes where about half of the
54 population of victims even do not aware of that they are carrying diabetes silently in the body .The growth rate
55 of diabetes patients is alarming in several middle income and emerging countries and Asian countries are the
56 major contributor for devastating growth rate of diabetes [2].

57 From the analysis of several health studies, it is known that the advance and predefined adequate proper
58 knowledge about the consequences of diabetes and better and more compact prediction solution may be very
59 effective to fight against diabetes in more convenient way and help to raise awareness among people.

60 World Health Organization (WHO) published a static based analysis and research-based report to focus and
61 intensify the real diabetes scenario of Bangladesh. From the recent meta-analysis conducted by WHO reviewers
62 showed that the recent threatening pervasiveness of diabetes among Bangladeshi civilian had increased in an
63 alarming rate, the report focused on dramatic increment sequence of growth rate from in 1995 to 2010 [3]. In
64 1995 the rate was only 4% which increased 9% in 2006 and until the year of 2010.

65 According to the analysis and prediction of the International Diabetes Federation based on the analysis of
66 several case-studies , the organization predict that the devastating rate will grow further and will be increased
67 about 13% by the year of 2030 [3].

68 By reviewing the previous documentations and reviewing several journals, it was confirmed that there is a
69 serious limitation in the field of diabetes research and predictive system because there are no available suitable
70 documentations or studies dedicated for this specific region. The prime drawback of Previous studies were that
71 the previous models were not designed properly and combination of attributes were not properly designed. Again,
72 the previous studies were bounded to specific region or focused on specific sex or gender.

73 The prime emphasis of the study is to obtain a full set of co-relating factors which are the prime responsible
74 attributes for diabetes and to establish a predictive model to predict and identify diabetes at an early age. This
75 model is best specially optimized for the south Asian counties like Bangladesh because to conduct this study a
76 lot of matters and factors regarding for the specific region were taken on consideration based on need and expert
77 opinion.

78 Therefore, there was a serious need for a specific model. According to expert opinion and WHO's Report
79 guideline, the primary goal was to identify each individual, household and related fixed or specified community
80 factors associated with the conditions. WHO found and expressed a significant connectivity or relationship with
81 diabetes and age. In most common term, older /middle aged people have the more chance to get attached by
82 diabetes because age is one of the prime differentiators for diabetes.

83 2 Fig. 1.1: Diabetes ratio around the world

84 From the result of previous study, it was confirmed that most of the diabetic affected population likely (40%) are
85 enough educated, have sufficient knowledge about diabetes and they belong to middle class income level, where
86 almost 13% participants were from lower income family. From the previous study, it was known that about 40%
87 of total diabetes population were receiving regular medical check-up and proper healthcare system.

88 Diabetes is known as a silent carrier and it is a carrier of several deadly diseases which can cause long term
89 health hazards. To maintain a good health score, it is needed to identify diabetes at primary stage and maintain
90 a proper diet and exercise chart. Again, the devastating growth rate of diabetes in this region, is very harmful
91 for the human resource management for the country as diabetes patients become unable to overtake heavy and
92 handy task [7] [9].

93 So, the method of prediction of diabetes at an early stage is very important and beneficial for the community.
94 There is no available preventive methods of totally cure the diabetes and root out the disease from the body, but
95 there is a well-defined solution to control the glycemic index and sugar of the body.

96 Again, By using several data-mining techniques, it is possible to predict the disease far early and assist doctors
97 and healthcare providers to reach in a better diseases management procedure. Analysts and researchers Patient
98 will also get food and exercise recommendation through this system.

99 3 b) Problem Definition

100 Diabetes is a wide spread disease and it has some common symptoms and attributes. Family history, Age,
101 Sex, BMI, blood pressure etc were taken into consideration to make a proper evaluation of model. The normal
102 measurement level of diabetes is fall between to 6.0 mmol/L during the time of fasting and it will cross the level
103 of 7.8 mmol/L after 2 hours meal.

104 Diabetes has 2 different types which include type 1 diabetes and type 2 diabetes. Diabetes has some specific
105 symptoms. These symptoms appear to the people, especially those with patients with type 2 diabetes, some of
106 these symptoms may appear lately. For the type 1 diabetes patients the symptoms may appear quickly and more
107 severe [4].

108 Some common symbol of type 1 and type 2 diabetes are [4]:

109 ? Increased amount of extreme thirst ? Increased amount of hunger [7] [12].

110 ? Sudden weight loss ? Frequently a chemical substance named ketones is found in the urine ? More Frequent
111 and unexplained urination [5] ? Decrement of vision gradually ? Get attacked by more and Frequent common
112 infections, like skin infections and infection in several sensitive organs [8].

113 From the result of various surveys and analysis, it was confirmed that Type 1 diabetes can develop in the
114 body at any indigenous period or age, though it often found in childhood stage. where Type 2 diabetes is more
115 widely spread to the middle-aged person and common in people older than 40 [4], though type-2 diabetes can
116 also appear at an early age. Diabetic diseases is classified into four category. Therefore, patient can have these
117 type of diabetes. These are given below:

118 4 Type 1 diabetes

119 The prime cause of type 1 diabetes is still unknown today. As per scientific documentations, combination of
120 genetic susceptibility and environmental factors are considered as the primary reason of Type-1 diabetes .In this
121 type, the immune system of the body surprisingly misunderstands and destroys the insulinproducing cells in the
122 pancreas. This action is hazardous for metabolic system because in this case there is only a little or no insulin
123 found in the body which is insignificant for metabolism. As a result, metabolism and energy transmission to the
124 body cell is hampered and extensive level of sugar found in bloodstream [4].

125 5 Type 2 diabetes

126 As per scientific documentations, in type 2 diabetes, body cells become resistant to the action of insulin. one
127 the other hand, the organ named pancreas cannot produce sufficient insulin for the body [4]. For a type-2
128 Diabetes, adequate exercise and proper diet plan is needed to manage the proper blood sugar level. Again, for
129 some specific case, doctors recommend insulin to some specific patients. Doctors and health scientists around
130 the world indicated that genetic factors, nature and environment plays an important role for creating diabetes.
131 Overweight and diabetes Type-2 has also strong relation.

132 6 Gestational diabetes

133 During the period of pregnancy, the placenta produces some dedicated hormones. These specified hormones
134 act against insulin [4]. Generally, in all the cases and types of diabetes, patients pancreas releases extra-more
135 insulin to control and manage the diabetes. But in some cases pancreas cannot emit extra insulin which causes
136 gestational diabetes [4].

137 7 c) Overview of the thesis

138 The responsible reacting factors were marked and identified based on several important factors and co-related
139 relationship. The findings and the results of Several statics and previous studies were extensively used to make the
140 proper evolution of the model. Then important information and findings from the results of previous successful
141 case studies were identified and sorted for future use. Attributes were selected with extensive care and based on
142 their contributions for developing diabetes in body. The expert opinions and doctors advice enlisted in several
143 health journals were taken into consideration to select the proper attributes. Again, participants were classified
144 and divided into several groups and different categories based on research demand. Several statistical evolution
145 and informative data were the prime source of data and patients real time data depending on the Complete list
146 of foods and different meal plan [0]. Based on the collected samples and evaluations of different attributes of each
147 and individual patients, the desired calorie need was taken into consideration based on patients need and health
148 need. If the diabetes patients follow the recommended diet chart and adequate exercise then it will be beneficial
149 to control diabetes.

150 8 d) Scope of the thesis

151 The thesis was done based on the evolution of several related attributes and their contribution towards the thesis.
152 The findings and recommendations of thesis will pave the way to find out a more prominent and trustworthy
153 solution for the diabetes patients to digenesis the disease far earlier than it appear and it will recommend a
154 optimum lifestyle needed for the diabetes patients. The lifestyle, food habit, exercise time and taken insulin can
155 be stored in a database for further analysis. Again, based on the comprehensive analysis and extensive data
156 analysis, prediction of risk factor of diabetes can be calculated by using our developed model. Risk factors and
157 the probability of patient's get attacked by diabetes can be predicted accurately to fight against diabetes in more
158 convenient way.

12 LITERATURE REVIEW A) CORRELATIVE FACTORS ON TYPE 2 DIABETES PREVENTION EFFORTS OF THE SENIOR HIGH SCHOOL STUDENTS IN MAKASSAR

9 e) Objective of the thesis

The primary goal of thesis is to identify the risk of diabetes at an early age to create awareness among the future diabetes patients and to manage the diabetes in much more pre-planned and organized way to fight against diabetes. As diabetes is a permanent diseases and there is no available solution to up-root diabetes from the body. The proper and well defined safety regulations can be ensured by regular assessments. Diabetic patient's recommended and optimum lifestyle was also suggested in this evaluation. It will also pave the way to reach in a compact solution by predicting diabetes earlier and upcoming diabetes victims will become more conscious about their habit and lifestyle to minimize the risk and to manage a better health index.

10 f) Organization of the thesis

Despite of the advancement of medical science, there is no permanent cure Diabetes and it is growing at an alarming rate which is cautious for the economical development of the country. Most of the times, the patient's health condition becomes worse of Diabetic Patients because they are often ignorant of risk factor and do not maintain a proper diet chart. So, the advance prediction of risk factor of diabetes can be life saving for the ignorant patients.

In the previous study, Many scientists used various kinds of machine learning techniques. Researchers around the world experimented and used several different types of classification algorithms. Several statistical techniques and mechanisms were used to predict diabetes in advance. Again, Doctors and Health experts also analyzed the performance of different algorithms and cross-validated the model. The previous approaches paved the way to reach in a compact solution.

In this paper, a custom designed well defined model along with a refined formula was proposed to identify diabetes at an early age and manage the proper health index in much more convenient way.

A well structured and efficient dataset was collected from the combination of various medium like Internet open data sources, survey results and questionnaires and all the data was stored in a integrated database to use it for further validation and future development of the model.

Extensive Synthetic and analysis of collected dataset was done based on the combination of various attribute. In this research, it was the primary goal to find out a proper relationship status and proportional or inverse-proportional relationship between the each and every reacting attributes. Then, the scientific evaluation and proper cross-validation process were done to recheck highest accuracy of the model.

11 II.

12 Literature Review a) Correlative Factors on Type 2 Diabetes Prevention Efforts of the Senior High School Students in Makassar

This study has found out the most common and successfully indicated related probable factors responsible for diabetes. The primary goal of the paper was to analyze associated factors and clauses related to DM specially for the level of teenage student in the city of Masakkar, Indonesia. In this study, the primary dataset was collected from high school students and age between 11-16 year students were highlighted and focused to determine the diabetes Meletus's impacts and related reasons to analyze the risks and the threads of diabetes for the teenager and to prevent it at an early stage. Data was collected in various methods like questionnaire, survey etc. The study is based on Indonesia, where DM prevalence is estimated increase from 8.4 million to 21.3 million between 2000 and 2030. The devastating growth rate diabetes affected patients is hazardous and it is indicating a highly health disaster. By analyzing the datasheet thoroughly, it was found that only 6 respondents (24.0%) had parent with lower or less standard education level where majority of respondents 189 in numbers had parent with high education level, consciousness in prevention efforts on Diabetes. In this paper Researchers noticed a common fact that among the participants of the study, those parent have higher or sufficient level of education, their children are more aware about the risk factors and they are adopting better prevention efforts to protect and fight against Diabetes. This study suggest that those people with low education level had "1.27 times" at risk of suffering DM than people with high education level From this survey, it was established that high incidence number of DM type 2 because of low of parental education level on prevention of DM type 2 incidence. Again, By analyzing the datasets, case studies and reports of several health sheets, it was seen that parental support plays vital role to maintain the goodheath index (standard) and it is a key promotor for creating prevention effort against Type-2 Diabetes among the teenager group. The result of the several data analysis and data sorting techniques showed a significant relationship between parental support with prevention efforts of DM type 2 among senior high school students. The study strongly found a link of The peer support and DM type 2 diabetes. The prime clause of the peer support was referred as providing relevant information, preventive measures on DM type 2.

In this paper, Authors observed and noted a significant relationship between hereditary parental educational awareness and health consciousness level, the strong relation of benefits perceived, barriers perceived, knowledge, peer support and social awareness and proper informational advantage can create a huge improvements and significant progress of prevention of DM at an early age

13 b) Designing Technological Interventions for Patients with Discordant Chronic Comorbidities and Type-2 Diabetes

In this present decade it is often found that Patients with Discordant-Chronic Comorbidities (DCCs) are likely to be attacked by multiple complex DCCs with a set of fully contradictory medicinal requirements, prescriptions, and guidance. This problem is disastrous because a medical professional should minimize the medication as per priority of diseases. So, there was a great demand for a help assistant system which can prioritize based on patient's health index and suggest an optimum solution for patients simultaneously. As part of the model, authors focused on developing and publishing a mobile application to evaluate the risk assessment scores on demand. The prime purpose of the application is to suggest and provide proper medication guidance based on the need and physical condition of every individual patient. The suggested application gathers a ton of useful health information, health reports, health index etc. data from every individual user, then analyses the data and enables patients to assist their conditions and treatments. It's often found in the medical data analysis that chronic conditions and apparent symptoms last for five or more months such as common diseases like Diabetes, Arthritis, or Depression, are becoming increasingly common in patients. Due to the habitat and integrated nature of diabetes and its typical conditions, patients are asked to play an active role in their treatments, schedules, and planning. From the health summary and results of several surveys, it is easily understood that the patients who do not follow or maintain the standard life guidance recommended for diabetes patients are at a greater risk. It's often found that the specific fact that the development of Discordant Chronic Comorbidities with multiple chronic conditions has become most common and often can be seen with the highest rate of co-connectivity which creates difficulties for healthcare assistants and desired patients when it comes to the terms of managing and controlling the impact of the managing conditions. To control and manage the state of diabetes, some plethora of available tools, apps, sensing devices, and various sensor tools only support the care and proper management of diabetes diseases. In previous studies, it is known that the proper diet sheet and diet management is the key factor to manage the proper status of diabetes. From the factbook, it is known that the prime challenge in studying patients with comorbidities arises from their compounding health factors and health assessment issues, which states often leads to the affected patients leading to more sickness and more spending time in hospital admission. This is the primary barrier of understanding the proper guidance of self-management assessments of their diseases and its associated risk factors. Based on interviews conducted with patients with Type 2 Diabetes and other Discordant Chronic Comorbidities, researchers designed a mobile application based on the barriers patients faced in successfully managing their treatment as well as some of the solutions they used or wished to use. The overall goal of this mobile application is to encourage patients to inbound in the application assessment exercise to improve their long-term health and quality of life.

By approaching forward on these certain topics, researchers emphasized and tried to develop this application and participate in testing with users with the ultimate hope of releasing this application to the general public. In addition, researchers are extensively looking to find out the optimum ways to manage diabetes in a more convenient way with the supervision of computer intelligence.

14 c) Recurrent Neural Networks with Non-Sequential Data to Predict Hospital Readmission of Diabetic Patients

It's recognized that hospital readmissions and vulnerable health index rates are the indicators of poor quality of Medicare, such as inadequate discharge planning and care coordination. It's often considered that frequent readmission and lower health index can be avoided by certain methods and propositions. In this paper, a Recurrent Neural Network model is carefully designed to predict whether a patient would be readmitted in the hospital or his/her health index parameters will be reevaluated to gain the highest productivity with several machine learning algorithms. In this study, it is found that RNN showed the highest prediction precision to target high-risk patients and prevent recursive admissions. Hospital readmission and degradation of health index, what will happen when a patient within a specified time interval or timeframe, who had been released from a hospital with a vital increment of health condition is admitted again. Again, a lot of research studies and publications proved that healthcare centers can engage in several activities like clarifying patient discharge instructions, coordinating with patient's health conditional index, handling with post-acute care providers, vibrant cleaning mechanisms to reduce the rate of readmissions of patients. In this paper, therefore, it raises a big question that which patient groups or which type of patients must be targeted to effectively reuse and redesign available resources for preventing readmission and to use the classified information for special case study. Many predictive and specially designed models that can predict accurately these are of a great help for hospitals all over the world as they can put extra efforts on high-risk patients and can decrease their readmission rates.

In this experimental procedure of research topic, the prime motto was to redesign, analyze, and construct a powerful model to predict exact numbers of diagnosis's measurements and different types of machine learning approaches and models were used to predict with the highest accuracy. In this case, especially Recurrent-oriented Neural Network outperformed the rest of the machine learning models in the prediction quality in the scale of productivity and accuracy. The knowledge, experimental results, and outputs gained from the journal can

effectively improve the traditional health system to target high risks patients, reduce rate of readmission and deliver better health care.

15 d) Development of Indian Weighted Diabetic Risk Score (IWDRS) using Machine Learning Techniques for Type-2 Diabetes

Medical experts and scientists have expressed their opinion that detection of diabetes at an early phase can be a lifesaving effort. Advance Diabetes relating factors and different screening tools such as Diabetes Risk Score (DRS) can effectively assist diagenesis and detecting diabetes accurately and help to prevent the diabetes among pre-diabetes phase at an early time before diabetes occurs. In current evaluations and assessments, Researchers have observed certain related issues in the available data and advocate the need to address the same. In this paper it's established a novel South-Asian regional Weighted Diabetic Risk assessments and co-relating factors. Different Machine Learning algorithms such as distance based clustering with Euclidean distance, k-means etc techniques were used by the researchers as a part of establishing a profound diabetes risk assessment tools to analyze the contribution of associated factors like blood pressure, age, stress and life quality BMI, diet, physical activity to boost up high plasma glucose level. In this paper ,the strategy to establish a strong and co-relating relationship between several differentiating factors , establishing a formula and then test and validates the formula with several test datasets to ensure the maximum accuracy. On an research World health organization referred that South-Asian countries citizen's are affecting on diabetes on this last two decades encounters at an devastating rate due to several depending factors. In this paper, the researcher collected datasets from various data sources, conducted surveys and used previously available data and information's to represent informational support. Data is collected form the south-Asian populations mostly from Bangladesh under the supervision of medical professionals. Several collected and trustworthy datasets were also used to strengthen the decision. Different types of Machine learning algorithms and advance data sorting principles are used for determining threshold values for various parameters when it was needed. A proper diabetes evaluation system or function is calculated for each factor like BMI, age, phenotypes, personal medical history, family history, diet, physical activity, stress and life quality. The genetic property, phenotype, lifestyle, working habit and some others factors are seriously related to diabetes. Different individual research, case studies and scientific studies have been proposed earlier by scientists to reduce the risk of diabetes to reduce the risks of diabetes, it's needed to differentiate the relationship between diabetes and different co-relating factors to fight against the risks of diabetes at an very early stage.

In this study, several reacting mechanisms, techniques and elements were successfully sorted which is very important to bring a new dimension in healthcare imagining prediction system. Different type of surveys, questionnaire, data synthesis techniques and computational intelligence were successfully used to identify and analyze the risk factors and their scores.

16 e) Study of Type 2 Diabetes Risk Factors Using Neural

Network For Thai People and Tuning Neural Network Parameters Advanced datamining techniques and analyzing tools are very Efficient to detect and predict diseases and their relating risk factors at an early age. In this paper, Researchers are trying to find out the relating factors which are mainly responsible for Type-2 Diabetes and proposed a relating solution to identify diabetes. In this paper a complete set of related factors which includes blood pressure, weight, body mass index, family history are considered as a primary factors. Again, smoking and alcohol consumption were considered as a strong co-relational factor based on their linked found in several researchers. To analyze and synthesis data BNN algorithm was as used. To collect datasets and sample information for training set about two-thousand samples of various health attributes were managed from BMC Hospital, Thailand. Based on previous learnings and previous research suggestions ,this paper found a strong relationship status and divided the risk level in there consequent stages i) low risk denoted as -1 point, ii) Medium denoted as between the range of -1 to 1 point and iii)High Risk was marked as the cautious level and contributed a single (1) scoring point for each risk based on different scale of measurement (unit) depending on the weighted contribution of linked factors like Family history, Age, Sex, BMI, blood pressure to make a proper evaluation of model. It was also added 1 point to the risk score for smokers and consumer of alcohol with timeframe of 4 weeks or more to summarize higher risk capability. By analyzing the documentations of the paper it established a U-shaped relationship with the consumption alcoholic drinks and smoking habit. The major findings, research analysis and conclusions was divided in two different portions. In this study, authors Initially identified the major related and responsible factors and made a complete a list of the proper corelating factors based on the evolution of collected datasets and previous records. Then , the all concerned factors and related terms were intelligently sorted and divided into three sophisticated categories based on their of different level of contribution to diabetes. Atlast, the study was concentrated on acquiring the learning rate with the tuning of BNN parameters.

This study concentrated in some vital factors and redefined the traditional reasoning methodologies which provides a better performance markup, higher accuracy level and better predictability compared to existing solutions and predictive analysis. From the result analysis of the paper, it was summarized that The prediction

334 accuracy of the proposed strategy was not as good as expected, but in this paper, authors focused on the best
335 optimum strategy to find out a better solution in future to predict diseases in much smarter way.

336 **17 f) Data-Based Identification of Prediction Models for Glu-** 337 **cose**

338 From Result of various Health surveys and analysis, it is known that Diabetes mellitus is one of the wide spread
339 diseases in all over the world .There are many co-effective factors which mostly responsible for the appearance of
340 Diabetes, but there is a general or common reason between every single diabetes patients is that they might have
341 deficiency in insulin production or insulin is not functioning well to improve the digestive system . It's advised
342 to all the DM patients to track the regular status of blood glucose to maintain a proper control of the glucose
343 count in the blood to become healthy and active. In this paper, it was observed that common barrier to control
344 the diabetes or glucose level by a semiautomatic model is to monitor the mechanism of glucose levels in blood
345 interact with insulin, diet intake or other factors interact with each other .In this paper, a set of traditional and
346 classical identification techniques such as Holt's smoothing, classical simple smoothing model was compare to
347 genetic programming models and techniques to evaluate the working efficiency of the model. Again, to maintain a
348 proper and balanced autonomous glycemic control, a glucose control and blood sugar level monitoring principles
349 and algorithms is extensively needed to outperform all existing solutions. In this paper, Authors put main
350 emphasis to develop a forecasting or predicting model to the evaluate the level ricks DM based on trustable
351 parameters like the real-time measurement of blood glucose. The Researcher also tried to predict the realtime
352 basics blood glucose monitoring system and this algorithm would successfully measure the blood glucose level
353 on the real time, it will analyze all the details and classified data and refer an insulin inhibitor system to supply
354 the necessary amount of insulin particles based on the patient's need and health condition on the real time. The
355 researchers have collected tons of data and heavily analyzed the data in terms of the space direction and the
356 power spec-trum. for the 10 in-silico patients.

357 In this study, the researchers have reached in a conclusion that the combine package of both the previous
358 Grammatical evaluation model and genetic programming is the best suitable techniques to predict, identify and
359 manage the issue. This proposed approach will bring a new revolution and new strategy to adopt with next
360 generation diagenesis and prediction modules to predict and fight against diseases at an early stage.

361 **18 g) Improve Computer-Aided Diagnosis with Machine**

362 Learning Techniques Using Undiagnosed Samples Now-a-days, different types of computer aided diagnostic tools,
363 various predication and machine learning algorithms are used to identify the root causes and responsible factors.
364 Again, to predict the risk of several fatal diseases in far advance and several computer aided tools and gadgets
365 are extensive used today to assist human to prevent diseases more effectively or to maintain a good health score.
366 To analyze and to understand thoroughly about a certain disease usually a huge number of diagnostic samples,
367 opinions, surveys etc are needed to be collected, examined and analyzed to sort out the effective responsible factors
368 and it's impossible for expert to analyze, simplify, synthesis this vast amount of information. That's why authors
369 of the paper put emphasis to develop a new technique to analyze data faster. In this study Researchers proposed
370 a effective semi-supervised machine learning algorithms named Co-Forest. Researched marked the new algorithm
371 as an extended and extensively modified version of existing machine learning algorithm named "Random Forest".
372 This algorithm is better for providing the analysis result and giving final hypothesis assessments compactly. [0].

373 Semi-supervised learning combines the both labeled and unlabeled data to extensively synthesis and extract
374 the required information to establish a reliable and trustworthy hypothesis. The study suggests that, To plan
375 or design a conventional methodology from scratch, the desired "co-training" data should be described by two
376 sufficient and redundant attribute subsets.[0]In this methodology, each of the section of classification-division
377 must be independent or act like as independent attribute and will capable of providing sufficient scopes unique
378 learning capability. In this paper, author denoted L as a tag of labeled set and U denote unlabeled set.

379 In this co-training mechanism, 2 different sets of classifiers are trained from Labeled data, after that
380 circumstance, each of sets should selects the most confident contents in Unleveled data to label from its point of
381 View[0].

382 This study extensively focused on the usability of unlabeled data to boost the extensive learning capability,
383 train from the unlabeled data and to save a lot of time in the field of health science. This approach is revolutionary
384 and it will bring more pace in sample data management process, comparing and analyzing a ton of information
385 in a short range of time frame.

386 **19 h) Diabetes Prediction Using Ensemble Perceptron Algo-** 387 **rithm**

388 Today's people food habit is largely dependent on ready-made, high sugar and high calorie enriched foods.
389 Medical experts and health scientist's advice the every suspected or affected diabetic affected person to diagnosis
390 the level of glucose in blood in a routine cycle, which is costly and time consuming. The extensive use of data
391 mining and machine learning algorithm with the assistance of computer aided system can effective be used to

21 J) DIABETES PREDICTION USING MEDICAL DATA

392 predict, identify and maintain diabetes in a controlled manner way. In this paper, authors proposed a whole
393 new machine learning methodology and mechanism which will effectively predict the risk of diabetes for the
394 unidentified patient and the working procedure of the new algorithm was tested on 3 different datasets to ensure
395 the effectiveness. Several A broad range of machine learning algorithms, data mining tools and specially designed
396 computer guided equipment are now effectively used to analyze medical data and to reach in a medical solution
397 for any specific diseases. In this paper, researches pave the new effective way to successfully diagnosis of disease
398 in a most convenient, compact and more rapid way. Several and different type of customized Machine learning
399 algorithm is now vastly used to analyze medical data and to reach in a medical solution for any specific diseases,
400 In this paper, authors suggested a new type called "Ensemble Perceptron Algorithm (EPA)" is proposed. This
401 profound attention marked on the algorithm because this methodology is used to utilize the classified method of
402 Perceptron Algorithm method of unseen data by a new proposed method with the help of Boosting algorithm.[0].

403 In this paper, Authors divided the working principle of the proposed method into 2 consequent phases. At
404 the session of training stage, a broad range of collected samples recognized as the training set are analyzed by
405 the perception algorithm in the cycle of arbitrary iterations and the help of packet algorithm and the cycle of
406 the iteration will come to and an end after identifying the best weight vector. At last, the discovered weighted
407 vector is kept in an array for further use. Then, by analyzing the weight vector, the profound analysis, score and
408 remarks of training sets then data and scores will be reevaluated and extensively calculated by using a described
409 function which was discovered in the paper [0]. Based on the extensive findings on several different domains, the
410 prime factors responsible for DM were placed according to the descending order for further use .In this paper,
411 authors considered "positive" for those resulted values which are greater than zero and rest of the values are
412 referred as negative. After all, the analyzed sample elements are need to be properly labeled and separated by
413 desired divisions as per the analysis of results achieved from the tests [0]. The prime approach of The Machine
414 learning algorithms is that it stores informational attributes of several participants for medical survey and then
415 analyze the data heavily to prepare to construct a model. In this study, the researchers identified the key factors
416 based on the proof of certain medical evidences and then suggested a profound relationship with diabetes and it's
417 associated risk factors. It is expected that, The learning and relational data gathered from the proposed model
418 can effectively be used in near future with certain modifications for medical prediction of undiagnostic patients
419 to accurately identification of the risk of the disease.

420 20 i) Prediction of diabetes based on personal lifestyle indica- 421 tions

422 Diabetes Mellitus develops in the body when there are higher or uncontrolled blood glucose level exists in the
423 blood-plasma cell for a long time. Recently, Researchers noticed that an uncontrolled level diabetes for a long
424 period of time can cause serious health hazards including blindness, kidney and renal failure to the affected
425 patients who do not maintain a standard pro-diabetic lifestyle. In this study, it was marked that diabetes has
426 a keen relationship with a person's attitude, lifestyle form factors. That's why the authors of the paper greatly
427 devoted to establish a profound and strong relationship status between diabetes and it's associated risk factors
428 like (age, Blood pressure, sex, Body mass index, waist circumference etc) and put their emphasis to develop a
429 model. In this study, various algorithms like a Chi-Squared Test of Independence and another data analyzing
430 technique named the "CART" (Classification and Regression Trees) were applied to test and analyze data. To
431 integrate this proposed model with computer based Data clustering system, the proper cross validation steps of
432 the process needed to be performed to ensure quality. From the analysis of previous study and research work,
433 it was identified that the people in the age margin of 45 years or above, having high blood pressure, BMI range
434 beyond the 25 and having a common genetic history of diabetes are the most vulnerable participants to be
435 considered and if the participants do not follow the proper diet chart or do not take proper physical exercise (
436 minimum 40 minutes /day) having these described attributes, these group of people have the highest probability
437 to fall in diabetes in the near future. To conduct the research work and to build a relationship model, Authors of
438 the paper collected the primary data about various relationship parameters like (age, BMI, BP, sex, sleep time,
439 Exercise time) from various sources by surveys, questionnaires and categorized and leveled the data in several
440 bounds based on the research requirement. In this study, it is found that for the categorical dataset, an algorithm
441 name "CART "prediction model performed the accuracy level of 75%.

442 Again, In this paper Researchers have investigated the collected datasets and found that High blood pressure
443 and unbalanced diet habit and consumption of junk food have a deep relationship with diabetes and this
444 assumption and profound relationship will bring a new era in healthcare diagenesis.

445 21 j) Diabetes prediction using Medical Data

446 Dr. D. Asir Antony Gnana Sin [1] in their research they presented a diabetes prediction system based on some
447 existing algorithms like Naive Bayes (NB), function-based multilayer perceptron (MLP), decision tree-based
448 random forests (RF). Some specified and custom techniques as well as some well specified algorithms were used
449 to find out a brand new and effective concept of new machine learning techniques and learning to bring out
450 a whole new process of diagnosis of diabetes in advance. Then this model was tested with different testing
451 methods such as 10-fold cross validation (FCV) and furthermore use percentage split with 66% (PS), and use

452 training dataset (UTD) to check the accuracy of the system. Some effective concepts-processing techniques were
453 used by the authors to increase the overall prediction precision level of the proposed model. They concluded
454 that the pre-processing technique produces better average accuracy for NB compared to other machine learning
455 algorithm. They gave the diabetes datasets into the machine algorithm (NB, RF, MLP) and noted the accuracy
456 with different test methods (FCV, UTD, PS). Then for removing the irrelevant feature through the preprocess
457 the dataset is given into the correlation-based feature selection. This is a looping process. They used WEKA
458 software and collected datasets from University of California, Irvine (UCI) machine learning repository.

459 This proposed approach and the learnings from the study will definitely bring a new revolution and brand new
460 effective strategy to adopt with next generation diagenesis and prediction modules to predict and fight against
461 diseases at an early stage.

462 **22 k) Prediction on Diabetes Using Data mining Approach**

463 Pardha Repalli et al. [2] in their research they predict how likely the different group of aged people are being
464 affected with diabetes based on their life style and for finding out factors responsible for the individual to be
465 diabetic. In this paper, authors considered some statistical datasets and information. Based on the learnings
466 from the datasets, some specialized data sorting techniques were used based on demand in order to understand
467 which group of aged people are being affected by this disease.

468 To establish a structure of the model and to find the co-relative factors , two algorithmic techniques were used
469 to predict accurately .They are i) binary target variable decision trees and ii) regression models . The best model
470 is selected by running multiple models such as step wise regression , forward regression , back ward regression,
471 decision tree with entropy. They have used the dataset of 50784 records with 37 variables.

472 Variable selection method was used by the Researchers to identify the target (input) variables for the study.
473 High Blood Pressure, Cholesterol Last check, Heart disease, Los all teeth, Years Education etc are important
474 input variables to predict the binary target variable. In this paper, Researcher used the parameter: age both as
475 nominal and quotative variable. By considering various different attributes like young age, middle age and old
476 age, authors divided and placed them in 3 separate categories. People with age above 45 years mostly affected by
477 diabetes, they concluded. Moreover they are suggested to visit for regular checkup, dental checkup and cholesterol
478 checkup frequently in order to control the diabetes. They also suggested young and middle age people for visiting
479 clinic in order to check whether they have diabetes or not. Age, High blood pressure, last cholesterol check, adult
480 BMI, Last flu shot and heart attack are the factors that also responsible for the individual to be diabetic.

481 **23 1) Predictive Analysis of Diabetic Patient Data using Ma-** 482 **chine Learning and Hadoop**

483 Diabetes Mellitus generally referred to as Diabetes is one of the form of Non Communicable Diseases. Diabetes
484 is so critical that it forms a long time complication situation associated with other types of diseases. For this
485 purpose a wise and definite way have to be found to reduce the overall impact related to diabetes by doing early
486 prediction of Diabetes patients history that can be datasets related to diabetes patients.

487 This paper proposed a systematic way that consists of machine learning and datasets analysis procedure
488 includes Hadoop and map reduce approach. This methods are used to analyze the huge amount of datasets and
489 find a pattern matching for it and also implements the missing data during analysis of data and this procedure is
490 followed for predictive analysis. For machine learning purpose supervised machine learning approach is followed-
491 Supervised machine learning is an approach where the overall input types and what sorts of output can be
492 generated or what sort of output can be produced in any of the cases is previously known. For this approach it
493 uses its previous datasets or past experiences to trained up itself and provides an expected result.

494 Hadoop or Apache Hadoop is one of the open source framework which forms a computer cluster in a distributed
495 way and it is massively used for analyzing massive amount of data in a very easy and less amount of time. For
496 analysis and processing of further data map reducing technique is followed ,it is a way of processing data in a
497 more reliable manner i.e this framework has the capability of processing data in a parallel and distributed way.
498 And it is done in two phases-Firstly it will take input of data (map phase) and will convert it into intermediate
499 data in the form of key value pairs and the next phase is the reduce phase where, by integrating and analysis of
500 all the key values from map phase it is converted to final output.

501 One of the vital and major factor that is used data analysis is all the attributes that are present in datasets
502 and used for analyzing and results obtained is used for predicting the future risk. During the dataset analysis
503 one of the major factor that causing problem is the values that are missing of any one of the attribute i.e null
504 values that can cause serious affects on results. So to overcome this situation classification clustering is used and
505 by using this technique missing values are replaced with their attribute mean. For this Missing Value Imputation
506 (MVI) algorithm is used by them. This algorithm firstly identify missing values from all attributes and then for
507 each attribute It calculates the attribute mean. Afterwards it impute missing values in dataset with attribute
508 mean and finally it combines missing values and datasets to produce the final result.

509 **24 m) Application of Data Mining Methods in Diabetes Pre-**
510 **dition**

511 Medical field refers and deals with accuracy. Without accuracy in this field it can cause serious negative effects
512 on patient.

513 This paper refers that early diabetes prediction can be done through the use of 5 types of Data mining
514 techniques-GMM, SVM, Logistic regression, Elm and ANN. Among the mentioned techniques ANN (Artificial
515 neural Networks) gives the highest accuracy rate and that result is much more closer to the actual result. ANN
516 is a method where it's consist of multiple layers or a cubical design, here the single path traverses its way from
517 front to back and this helps in resetting weights on the frontal neural units. ANN includes Layers and network
518 functions. The ANN consist of or configured of three layers namely-input, hidden and output. Firstly the input
519 layer or neuron defines all the inputs that will be given and this inputs are non other than all the attributes of
520 the datasets. According to the paper they have used 7 attributes so their neurons is also 7. Hidden layers receives
521 inputs from input layer and provides output to output layer. The most important work of hidden neuron is, it
522 assigns a weight for the input neurons and this assigned weights shows the relevance and importance of particular
523 and specific input to hidden neurons. Mathematically it can be defined as a neurons network function $f(X)$ is a
524 combination and composition of other function $g_i(x)$ and this can be again defined as composition of some other
525 function. The most widely composition is the non linear weighted sum where $f(x)=k(\sum w_i g_i(x))$ where K is
526 the activation function i.e it's a predefined function .The activation function provides a small out change when
527 a small change is made in the input. In this paper they have used ANN to predict the diabetes and the result
528 is 0.89 which is closer to actual result and this result is obtained when the hidden layer number is 2 and hidden
529 neuron is 5. That is it is found that by using ANN method it gives highest accuracy rate of 89%.

530 **25 n) A Clinical Perspective**

531 Diabetes is one of the common type of diseases where the blood sugar level in body become immensely high it
532 generally of two types namely type 1 and other one is type 2.

533 Type 1: Type 1 is a kind of diabetes in where it is a discontinuation or disorder of glucose regulation and
534 it is characterized by autoimmune destruction of the pancreatic beta cells that produces insulin and it leads to
535 hyperglycemia and it have higher tendency to ketoacidosis. It is more general and seen in among children but in
536 many case it may appear at any age. Genetic marker and the presence of antibodies can assist to identify diabetes.
537 Antibody markers of autoimmunity that is against beta cell includes autoantibodies islet-cell and autoantibodies
538 against insulin, decarboxylase, glutamic acid or tyrosine phosphates IA-2 and IA-2?, and ZnT8.3.Containing at
539 least one or more than one of this are present during fasting hyperglycemia it was initially detected in persons
540 where 85% to 90% of people can eventually contain or may develop type 1 diabetes. It is found that some patients
541 and mostly children and adolescents contains ketoacidosis as the first symptom of this disease. In less common
542 cases and typically in older patients, it can present with the mild fasting hyperglycemia or diminished glucose
543 level tolerance. T1 diabetes is not a linear progression disease but it progress at a variable pace in different
544 patients. Symptoms and sign including higher level insulin deficiency and hyperglycemia include polydipsia,
545 fatigue, weight loss, polyphagia and polyuria. This are causing defective transport of glucose from the blood
546 vessel/stream into body tissues and it results in increased glucose levels in the blood and moreover it elevates
547 glucose in the urine and concomitant calorie and fluid losses with the urine. For this when insulin level falls down
548 to such a low level lipolysis cannot be able to suppressed and products containing fat metabolism naming ketone
549 bodies is accumulated in the blood and due to hyperventilation it leads to metabolic acidosis and compensatory
550 respiratory alkalosis.

551 **26 o) Application of Data Mining Methods in Diabetes Predic-**
552 **tion**

553 In any sort of medical field the most important factor is all about accuracy. Without accuracy in this field it can
554 cause serious negative effects on patient. So accuracy is the most important factor.

555 According to this paper early prediction of diabetes is made through the use of 5 types of Data mining
556 techniques-GMM, SVM, Logistic regression, Elm and ANN. Among all the five techniques ANN (Artificial neural
557 Networks) provides the highest rate of accuracy ANN is a method where it's consisted of multiple layers or a
558 cubical design, here the single path traverses its way from front to back and this helps in resetting weights on
559 the frontal neural units. ANN includes Layers and network functions. The layers are-Input layer, hidden layer,
560 output layer. The input layer or neuron defines all the inputs that will be given and this inputs are non-other
561 than all the attributes of the datasets. According to the paper they have used 7 attributes so their neurons is also
562 7 Hidden layers receives inputs from input layer and provides output to output layer. The most important work
563 of hidden neuron is, it assigns a weight for the input neurons and this assigned weight shows the relevance and
564 importance of particular and specific input to hidden neurons. Mathematically it can be defined as a neurons
565 network function $f(X)$ is a combination and composition of other function (x) and this can be again defined
566 as composition of some other function. The most widely composition is the non linear weighted sum where
567 $f(x)=k(\sum w_i g_i(x))$ where K is the activation function i.e it's a predefined function. The most help and useful

568 characteristic of this activation function is that it provides a small out change when a small change is made in
569 the input. In this paper they have used ANN to predict the diabetes and the result that was assuming to be the
570 best is 0.89 and it is obtained when the hidden layer number is 2 and hidden neuron is 5. That is it is found that
571 by using ANN method it gives highest accuracy rate of 89%.

572 **27 p) Blood pressure and ageing**

573 Increase in blood pressure with the increasing of age can of many varied factors and it is also depended on
574 many cases like lifestyle and living environment of different person. BP seems to be rise or fall with age. It is
575 of two types systolic and diastolic blood pressure in short SBP and DBP. With the increase of age the blood
576 pressure is associated mostly with the changes relating with arteries, large artery stiffens and also with increase
577 of risk related to cardiovascular the blood pressure also rises. In case of aged person with the effect of increase
578 of systolic and decrease of diastolic pressure related to blood there causes a risk of increasing pulse pressure
579 that consequences in blood pressure. SBP dramatically and continuously starts to increase between the age of
580 30>above and in case of DBP it does not show a continuous pattern but it varies with age until fifth decade it
581 starts to rise but suddenly starts falling at the age of 60-84. According to this paper a definite level of age is
582 chosen for identifying the BP, in case if it is classified within different range of ages it would be much more easier
583 to identify the provable causes of increasing or decreasing of BP.

584 **28 III. Diabetic Patient Data Management and Support System**

585 **a) Introduction**

586 The primary process of the research was to determine the principle co-relating factors and their contribution
587 and impact toward the diabetes. To conduct the research, previous learning and knowledge base of previous
588 health reports were considered to reach in a decision. Health information and datasets are collected from various
589 different sources like direct questionnaires, results of conducted online surveys, previously available datasets and
590 available health samples of diabetes patients on various health portals and recognized health journals. Samples
591 and essential information or health data based on several attributes were collected from different sources from the
592 available information of more than 450 participants of various health surveys and questionnaires. Then all the
593 necessary information and parameters were carefully sorted and selected. After extensive sorting and filtering
594 incomplete, less trustworthy and irrelevant information were discarded. After all, relevant information of 300
595 participants collected from various sources from the time period of (2011-2019) years were placed and stored in
596 a dataset for this research purpose. This dataset was the primary information source of this research. Some
597 principal attributes were taken into consideration. The prime attributes are age, gender, Blood pressure, height,
598 weight, BMI, sleeping time and exercise time of each and individual patient.

599 The output of the research work is to build a sustainable model which is essential to predict diabetes with
600 highest precision and detect the chance of getting diabetes in near future. This system will also suggest the
601 optimum lifestyle and exercise suggestion to the participants

602 **29 b) Diabetes patient data analysis model**

603 The performance evaluation of a health model broadly dependent on four variables. They are Participant's real
604 time health information, Participant's food habit, Participant's exercise sheet, Participant's medical feedback. A
605 proper health supervision for a diabetic patient is provided by this model as this model is capable of predicting
606 the risk of diabetes in advance and it will help the upcoming diabetes victim by providing advance alert to them.
607 In this paper, the attributes like BMI, height, weight, sleeping time and working hours or weekly bases exercise
608 time, blood pressure were identified as the prime reacting factors. These attributes are the dominant factor.

609 Calorie intake and exercise time are also important factor for the diabetes.

610 Proper management of diet system and medication can treat and manage diabetes in proper way.

611 The patient containing extensive blood sugar may be suggested to take insulin. This approach will help to
612 manage the proper health status and control the weight, blood sugar and calorie consumption for specific patients.

613 **30 c) System Architecture**

614 Modeling of system is consisting of designing the system, processing the system architecture and integrate the
615 proper modules and interfaces based on system requirements.

616 The approach and process is divided in several consequent steps. First of all, a diabetes dataset is carefully
617 prepared and then proceed the dataset as input to the specified system analyze the data with exact precision.
618 Then, this system is designed to perform in ready state to analyze based on input data. A well specified model
619 and properly guided mathematical equation with proper optimization of the backend calculative format is placed
620 in the backend of the system to analyze data. Certain terms and conditions are also set in the system to work
621 efficiently. After taking input data from the participants, then the system measures the input data based on
622 the developed mathematical equation. At-last, the system provides a prediction with a precise risk estimate in
623 percentage for each individual patient. Then, this system will provide the optimum exercise goal and lifestyle
624 for each and every individual patient. The medical experts and data scientists can use this prediction for further

31 FIG. 3.1: SYSTEM ARCHITECTURE D) INTEGRATED DATABASE DESIGN

625 improved diagnosis process. However, the system is quite accurate to analyze data and to predict data for each
626 and every individual patients. Moreover, the effectiveness of the proposed system can further be improved by.

627 **31 Fig. 3.1: System Architecture d) Integrated Database** 628 **Design**

629 To conduct this research and to prepare the dataset, some conditions were taken into consideration. These
630 conditions and research terms were carefully selected based on the experimental approaches and previous leanings
631 of related research works.

632 In this Integrated datasheet completely emphasis on various health parameters of the patients. Again, this
633 dataset provides a minimalistic idea about the lifestyle of the participants based on the analysis of various different
634 parameters. By this approach, it is possible to identify the probability of diabetes at an early age.

635 To prepare the model realistic data was set and higher and lower bound values were carefully selected based
636 on realistic data set, web source and medical fact data sheet. The values are carefully analyzed and not a single
637 input in this range is out of the topic, it was confirmed that the participants having the fasting blood sugar range
638 below the 3 mmol/L have the lowest.

639 ? Possibility to fall in diabetes in near future. The Fasting blood sugar range from 3 mmol/L to 10mmol/L
640 was taken into consideration for this system.

641 ? Participants Blood Sugar (Random): Participant's blood sugar after 2 hours phase is likely an important
642 indicator .The Random blood sugar range from 5 mmol/L to 30mmol/L was taken into consideration for this
643 system. The random sugar should be noted with highest professionalism because any malfunctioned result or
644 data input will change the whole result of prediction probability .The random blood sugar range above 10mmol/L

645 is a serious indicator of getting diabetes. ? Participants Blood Pressure: From the analysis of several medical
646 studies, scientists have found a significant connection of Participant's blood pressure with chance of patient's
647 getting diabetes. The normal range of Systolic blood pressure is less than 120 mmHg and Diastolic blood pressure

648 is less than 80 mmHg. ? Participants Sleeping-time: In recent studies, health scientists have found specific link to
649 sleeping hour with the probability of getting the chance of diabetes. From the analytical reasoning of the dataset,
650 it was found that balanced sleeping time has a inverse-proportional relationship with diabetes. The participants

651 sleeping time were counted in hours on weekly basics. ? Participants Exercise-time: Exercise is the key factor
652 to control the glucose level of the blood. Optimum exercise plan can significantly lower the blood glucose level
653 and chances to get attacked by diabetes in near future. So, Exercise time has a inverse-proportional relationship

654 with the blood glucose level. The participants working or exercise time were counted in hours on weekly basis.

655 In our database design we have generated following attributes. The generation process has been discussed
656 below: ? Participant's Age: Patient's age is one of prime factor for this study. From the analysis of the dataset
657 and the previous learning suggested that age has a very close relationship with diabetes. From the analysis it

658 was observed that the people of age range belongs to 40 years to 60 years [5] have the highest risk to be get
659 attacked by diabetes and the people of age below 40 years and above 65 years have comparatively the lower risk
660 percentage. ? Participant's BMI: Body Mass Index(BMI) is an important indicator of Health index. To calculate
661 BMI it is needed to collect Height and weight of individual patients.

662 To calculate BMI it was needed to record height and weight of each and every individual participants. In this
663 system, it was considered the existing "Guinness world records" fact book to find out the tallest and smallest
664 heighted people's height to set the lower and upper bound of the height for the model. Though most of the
665 participants belonged to the height range of 5 feet 3 inch to 5 feet 11inch range.

666 The generalized formula to calculate BMI: $BMI = \text{Weight} / (\text{Height})^2$

667 Where Weight is calculated in Kilo-gram (Kg) and Height is calculated in Meter(m). That's why, taller
668 patients with moderate weight have likely to face less risk of getting diabetes than the shorter participants with
669 moderate weight. To calculate BMI, it was needed to collect weight and height of the participants. In this study,

670 it was considered the BMI range from 10 kg/m² to 50 kg/m² .Where the participants having the BMI range of
671 18.5 kg/m² to 25 kg/m² are considered to be healthy and participants having BMI above 30 kg/m² are at a risk
672 of getting diabetes in near future.

673 ? Participant's Gender: Participants gender is a related factor to estimate the risk for individual patients.
674 Patients gender is a discriminating factor for the analysis of dataset. Female patients have different type of
675 diabetes characteristics and many women fall in temporary diabetes which is called gastrointestinal diabetes. So,
676 Data was collected from both Male and Female participants.

677 Participants Blood Sugar (Fasting): Participant's blood sugar at fasting phase is likely an important indicator
678 .It is one of the prime concern for the analyzing diabetes because patients having higher blood sugar in fasting
679 phase likely to fall in diabetes in most of the times. By analyzing the dataset and previous study In this graph, it
680 represents the risk of diabetes occurrence was compared with the relational attribute Age .In this dataset what was

681 used a primary data source for the research , the Age range was between the range of 1year to 80 years of a different
682 groups of male and female. Blue color plotted line is representing the Age (attribute). As per the information
683 of dataset, Age started from the numerical value of 10 years old and finished at the ending point of 80 years. In
684 this graph, Age was compared with surveillance participants diabetes status test_result. The test result has two
685 different values i) Tested positive which is denoted as numerical value " 13.0 " (Yes/diabetes tested positive) to

686 make and plotting the intercepting graph flatters and to make it more flexible to compare differentiating points of
 687 the graph , for ii) Tested Negative which is denoted as numerical value " 7.0 " (False/diabetes tested Negative) to
 688 make and plotting the intercepting graph flatters and to make it more flexible to compare differentiating points
 689 of the graph. From the visual inspection of the graph, it is clear that age has a proportional relationship with
 690 test_result(negative/positive).Diabetes risk occurrence is heavily linked with the age. The persons /participants
 691 under the age of 26 years have the lowest risk probability and the age range between 26-40 years have the lower
 692 possibility. The age group of above 45 years old people have the highest risk of diabetes occurrences.

693 From the analysis of the graph and previous studies , it is confirmed that older people have the higher risk
 694 of diabetes occurrences. Diabetes Risk Occurrence ? participant's Age. Diabetes Risk Occurrence = K_1
 695 *participant's Age (4.1) Where k_1 is a constant.

696 32 Body Mass Index (BMI):

697 33 Fig. 3.3: Body Mass Index (BMI) vs Surveillance partici- 698 pants diabetes status test_result

699 In this graph, it represents the risk of diabetes occurrence was compared with the relational attribute Body Bass
 700 Index(BMI) .In this dataset what was used a primary data source for the research , the Age range was between
 701 the range of 16.5 kg/m² to 42 16.5 kg/m² of a different groups of male and female. Blue color plotted line
 702 is representing the BMI (attribute). As per the information of dataset, Age started from the numerical value
 703 of kg/m² and finished at the ending point of 42 kg/m² .In this graph, BMI was compared with surveillance
 704 participants diabetes status test_result. The test result has two different values i) Tested positive which is
 705 denoted as numerical value "13.0" (Yes/diabetes tested positive) to make and plotting the intercepting graph
 706 flatters and to make it more flexible to compare differentiating points of the graph, for ii) Tested Negative which
 707 is denoted as numerical value "7.0" (False/diabetes tested Negative) to make and plotting the intercepting graph
 708 flatters and to make it more flexible to compare differentiating points of the graph. From the visual inspection
 709 of the graph, it is clear that BMI has a proportional relationship with the surveillance participants diabetes
 710 status test_result (negative/ positive). Diabetes risk occurrence is heavily linked with with BMI. The persons
 711 /participants under the BMI of 21 kg/m² have the lowest risk probability and the BMI range between 22 kg/m²
 712 -28 years kg/m² have the moderate risks. Having the BMI above 31 kg/m² , such group people have the
 713 highest probability of risks of diabetes occurrences. From the analysis of the graph and previous studies, it is
 714 confirmed that people having the BMI >32 kg/m² people have the higher risk of diabetes occurrences.

715 Diabetes Risk Occurrence ? participant's BMI (body mass index).Diabetes Risk Occurrence = K_2 *
 716 participant's BMI (4.2)

717 Where k_2 is a constant Blood Sugar (Fasting): In this graph, it represents the risk of diabetes occurrence
 718 was compared with the relational attribute Blood Sugar (Fasting) .In this dataset what was used a primary data
 719 source for the research , the Blood Sugar (Fasting) range was between the range of 3.9 mmol/L to 9.1 mmol/L of
 720 a different groups of male and female. Blue color plotted line is representing the Blood Sugar Fasting (attribute).
 721 As per the information of dataset, Blood Sugar Fasting started from the numerical value of 3.9 mmol/L and
 722 finished at the ending point of 9.1 mmol/L.In this graph, Blood Sugar Fasting was compared with surveillance
 723 participants diabetes status test_result. The test result has two different values i) Tested positive which is denoted
 724 as numerical value "13.0" (Yes/diabetes tested positive) to make and plotting the intercepting graph flatters and
 725 to make it more flexible to compare differentiating points of the graph, for ii) Tested Negative which is denoted
 726 as numerical value " 7.0 " (False/diabetes tested Negative) to make and plotting the intercepting graph flatters
 727 and to make it more flexible to compare differentiating points of the graph. From the visual inspection of the
 728 graph, it is clear that Blood Sugar Fasting has a proportional relationship with test_result (negative/positive).
 729 Diabetes risk occurrence is seriously linked with with Blood Sugar Fasting. The persons /participants under the
 730 Blood Sugar (Fasting) range of 4.2mmol/L have the lowest risk probability and the Blood Sugar Fasting range
 731 between 4.2mmol/L to 5.1mmol/L have the moderate risks.

732 From the analysis of the graph and previous studies, it is confirmed that people having the Blood Sugar Fasting
 733 >6.0 mmol/L people have the higher risk of diabetes occurrences. Diabetes Risk Occurrence ? participant's Blood
 734 Sugar (Fasting).

735 Diabetes Risk Occurrence = K_3 * participant's Blood Sugar (Fasting) ??4.3) Where k_3 is a constant Blood
 736 Sugar (Random): In this graph, it represents the risk of diabetes occurrence was compared with the relational
 737 attribute Blood Sugar (Random). In this dataset what was used a primary data source for the research, the
 738 Blood Sugar (Random) range was between the range of 4.1 mmol/L to 18.5mmol/L of a different groups of male
 739 and female. Blue color plotted line is representing the Blood Sugar Random (attribute). As per the information
 740 of dataset, Blood Sugar Random started from the numerical value of 4.1 mmol/L and finished at the ending
 741 point of 18.5 mmol/L.In this graph, Blood Sugar Random was compared with surveillance participants diabetes
 742 status test_result. The test result has two different values i) Tested positive which is denoted as numerical value
 743 " 13.0 " (Yes/diabetes tested positive) to make and plotting the intercepting graph flatters and to make it more
 744 flexible to compare differentiating points of the graph, for ii) Tested Negative which is denoted as numerical
 745 value " 7.0 " (False/diabetes tested Negative) to make and plotting the intercepting graph flatters and to make

35 RESULT AND ANALYSIS

746 it more flexible to compare differentiating points of the graph. From the visual inspection of the graph, it
747 is clear that Blood Sugar (Random) has a proportional relationship with the surveillance participants diabetes
748 test_result(negative/positive).Diabetes risk occurrence is seriously linked with with Blood Sugar (Random). The
749 persons/participants under the Blood Sugar (Random) range of 4.4mmol/L have the lowest risk probability and
750 the Blood Sugar Fasting range between 5.4 mmol/L to 6.1mmol/L have the moderate risks. From the analysis
751 of the graph and previous studies, it is confirmed that people having the Blood Sugar (Random) > 7.0 mmol/L
752 people have the higher risk of diabetes occurrences. In this graph ,it represents the risk of diabetes occurrence
753 was compared with the relational attribute Sleeping time. In this dataset what was used a primary data source
754 for the research, the Sleeping time range was between the range of 4 hours/day to 14hours/day of a different
755 groups of male and female. Blue color plotted line is representing the Sleeping time/day (attribute). As per
756 the information of dataset, Sleeping time started from the numerical value of 4 hours/day and finished at the
757 ending point of 14 hours/day .In this graph, Sleeping time was compared with surveillance participants diabetes
758 status test_result. The test result has two different values i) Tested positive which is denoted as numerical value
759 " 5.0 " (Yes/diabetes tested positive) to make and plotting the intercepting graph flatters and to make it more
760 flexible to compare differentiating points of the graph , for ii) Tested Negative which is denoted as numerical
761 value "3.0 " (False/diabetes tested Negative) to make and plotting the intercepting graph flatters and to make it
762 more flexible to compare differentiating points of the graph. From the visual inspection of the graph , it is clear
763 that Sleeping time has a inversly proportional relationship with the surveillance participants diabetes status
764 test_result (negative/positive). Diabetes risk occurrence is seriously linked with Sleeping time. The persons
765 /participants having sleeping time range between 6 hours/day to 8 hours/day have the lowest risk probability.

34 Diabetes

766
767 From the analysis of the graph and previous studies, it is confirmed that people having the Sleeping time >
768 8 hours/day for a week & Sleeping time < 5.5 hours/day for a week people have the higher risk of diabetes
769 occurrences. Step 4: passing the converted values into desired variables;

770 Step 5: starting of calculation by using the passed variables values into the derived equation

771 Step 6: Analysis Report or Result is received.

772 Step 7: Comparing the predicted calculation with predefined sets of terms and conditions Original result
773 is equal to multiplication of (Constant value , Age, BMI, fasting sugar level, random sugar level, systolic and
774 diastolic bp) which is divided by multiplication of sleep and exercise time. Step 8: Displaying the predicted result
775 and risk evaluation to the user

776 Step 9: Ready for further analysis of different inputs IV.

35 Result and Analysis

777
778 For checking the Diabetes occurrence percentage rate we have used a computer programmed system which is
779 developed according to our mathematical model. All the required attributes that we are using are taken in
780 consideration for giving input into the system and from that we get our diabetes occurrence percentage rate. For
781 the overall procedure 28 sets of data are given input into the system starting from age 11-77 yrs. Afterwards
782 by using the acquired occurrence percentage rate for every individual sets of data, graphs are prepared. The
783 graphs show the comparative analysis of diabetes occurrence rate with individual attributes. Here for every
784 individual graph Blood sugar level(random time) and Blood sugar level(fasting time) are taken in consideration
785 because this two attributes contributes the most crucial part for occurrence rate change because with a small
786 change in these attributes overall occurrence rate changes at a higher or lower rate. From the above Exercise
787 time (min) VS Occurrence percentage rate graph it is found that with higher exercise time and blood sugar level
788 (random/fasting) less than 7 have a less chance of diabetes occurrence and from the graph it is also found when
789 exercise time is 40 min and blood sugar level above 7 have a occurrence rate of 55 % and again with a decrease
790 of exercise time to 20 min with a similar blood sugar level the chance of occurrence increases by 5%. So with
791 less exercise time and having higher blood sugar level increases the chance of diabetes occurrence. For general
792 cases sleeping time is inversly proportional to occurrence rate that is with the increase of sleeping time diabetes
793 occurrence chance will be decreased.

794 From the above graph it is seen that for sleeping time of 11hrs the diabetes occurrence rate is 4.45% but that
795 occurs if the blood sugar level is less that if below 7. But if the blood sugar level is high sleeping time have a
796 very little effect on the overall occurrence rate as it is found from the graph when sleeping time is 10hrs and
797 blood sugar level(random) is 17 and blood sugar level(fasting) period is 9 in that case it has the highest chance
798 of diabetes occurrence. In this section an overview of our developed system is shown. There are eight input
799 fields for the user. All the inputs will be in standard unit of these parameters. Users will input their data in
800 the text fields in proper formatting. After clicking the check result button the front end will collect the form
801 data and will place them in some variables and it will pass all variables to the back-end system to analyze data
802 and generating a result. In the back-end the equation equates values and calculate the occurrence percentages
803 of diabetes based on the mathematical model. Figure ??1 shows the User Interface developed in this research to
804 identify the occurrence of Diabetes in human body.

805 V.

36 Conclusion a) Summary of the thesis

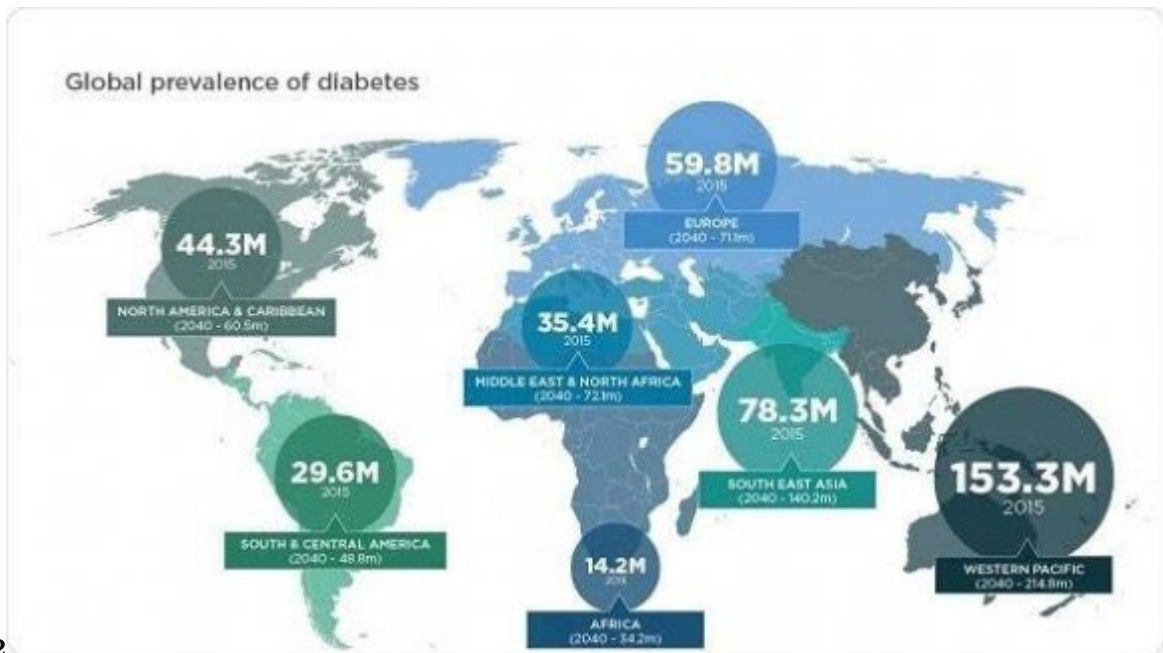
The primary goal of the developed model is to identify the occurrence rate of diabetes at an early stage with highest precision. Therefore, to identify the crucial factors for the thesis work a largesets of attributes were taken into consideration and after extensive analysis and scientific evaluations between the attributes, some attributes were finally selected to establish a scientific based mathematical equation which is combining all the terms, co-relations and all factors in a single mathematical equation for better and fast predictability. Using machine learning and data analysis techniques, it was established that the prediction score from the developed model matches closely with previous results. The model will provide valuable result and it will be helpful to identify diabetes occurrence rate with a less amount of diagnosis time and lowest cost consumption. Though the system has some error tolerance issue but after successful experimental and testing phase, the quality of data analyzing model and software system got better and became more reliable for accurate prediction.

37 b) Findings of the thesis

To conduct the research work , a huge number of case studies were analyzed and 50 more related journals, health science articles, analytics, survey reports were thoroughly studied to find out the actual reason of diabetes occurrences in human body and in this paper 8 co-relational actors were indicated and their co-relationship , bindings and contribution towards the diabetes was identified and marked .Then a complete mathematical term is established based on the previous knowledge, analytical attributes synthesis and based on mathematical terminology. Established mathematical equation and concepts were combined in a single equation with a universal constant formatting All the mathematical terms were reverified in several techniques like plotting different attributes in graph to identify the correct relationship. A dataset of 250 participants of different age, groups and communities were selected for the case study and testing of the developed system. From this study it was confirmed that age is the most dominant factor and then random blood sugar level is a clear indicator of the diabetes status or diabetes level .All the attributes studied in this research like age, BMI, blood sugar, blood pressure, working and sleeping time have some contributions on diabetes risk score. A person can easily minimize the risk score by adjusting his/her life status, daily habits, food-calories intake and scaling an ideal exercise or sleeping time. Though diabetes is not preventable but the blood sugar level of any patient can easily be maintained in ideal level by inducting an ideal food, diet chart, balanced sleep and working hours and a good quality of life. The risk of diabetes will be optimized by an ideal lifestyle recommended by health nutrition experts and medical professionals.

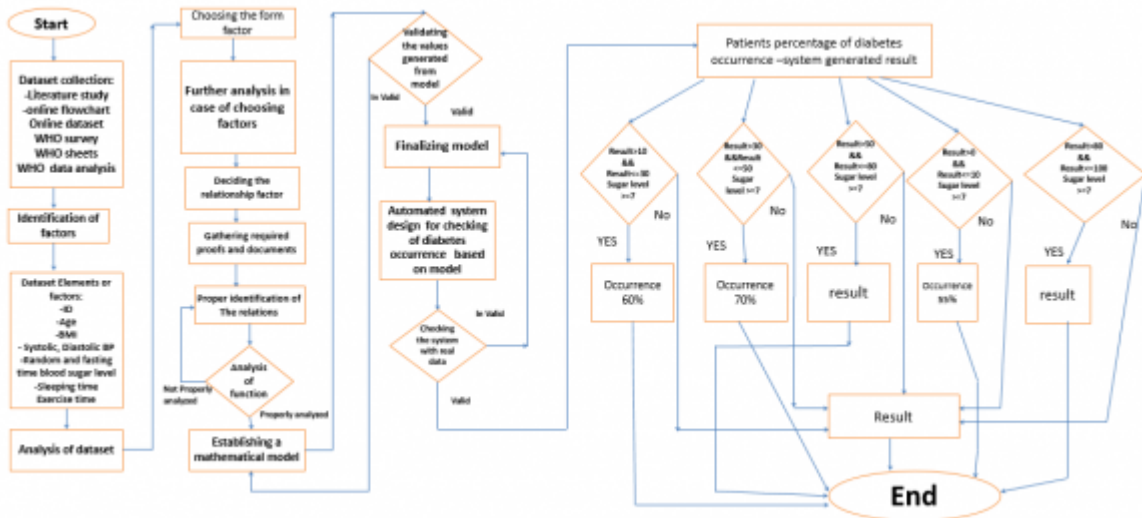
38 () G

Year 2021 c) Future Scope of the thesis In this developed model, an estimated compulsion proportion between all the attributes were selected and all the attributes consist of same weighted values. Some attributes like Age and working time are primary deal breaking factors but in this work , genetics property of diabetes was not considered due to lack of proper evidence ,lack of previous studies .In future work, genetic inheritance factor will be considered for further detailed analysis .In this study, a software system is developed with manual input checking and it shows the output of risk percentage .In future work, a complete data book for every patient will be added. Interface of the computer system will be further modified. Social media's add-ons can also be added so that the system can easily fetch user data from social account for further analysis with less user input, which will become more user friendly .Our system can be also integrated with other health monitoring devices like smart watches like Apple Watch 3 or others which will be very effective to sync user data in real time basics and to store a portfolio for the patients .This system will be ready to sync data from other input sources, health devices and generate results based on the users input .Then the results will also be sent to added IoT gadgets for better health management. In the next edition our software will predict with more precision and accuracy with the extended use of IOT connected devices which will help patients to maintain an optimal lifestyle and balanced diet. In future edition, our developed software and ecosystem will also provide a better health analytic and better health management system.



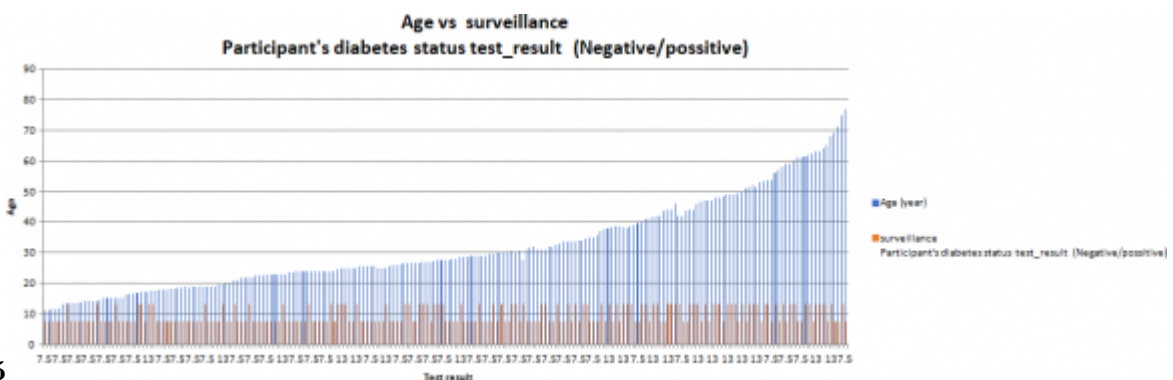
32

Figure 1: Fig. 3 . 2 :



34

Figure 2: Fig. 3 . 4 :



35

Figure 3: Fig. 3 . 5 :

3638

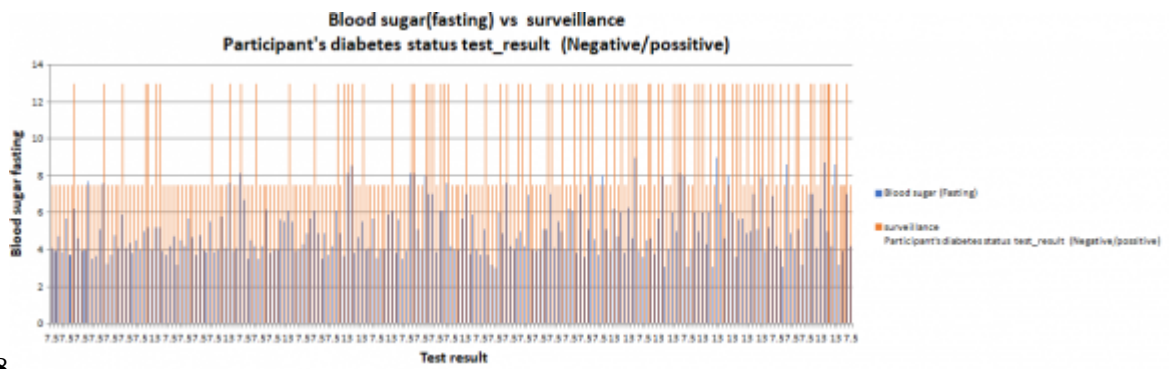


Figure 4: A Fig. 3 . 6 : Fig. 3 . 8 :

41

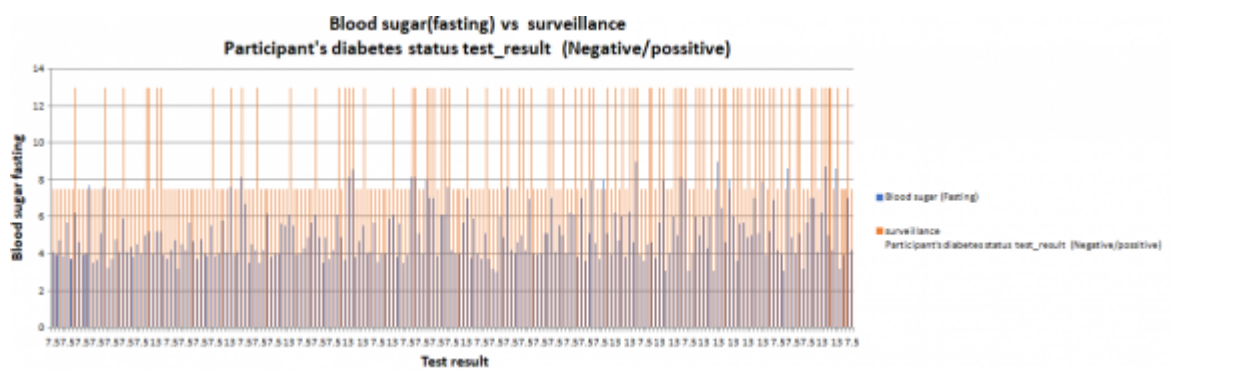


Figure 5:

41

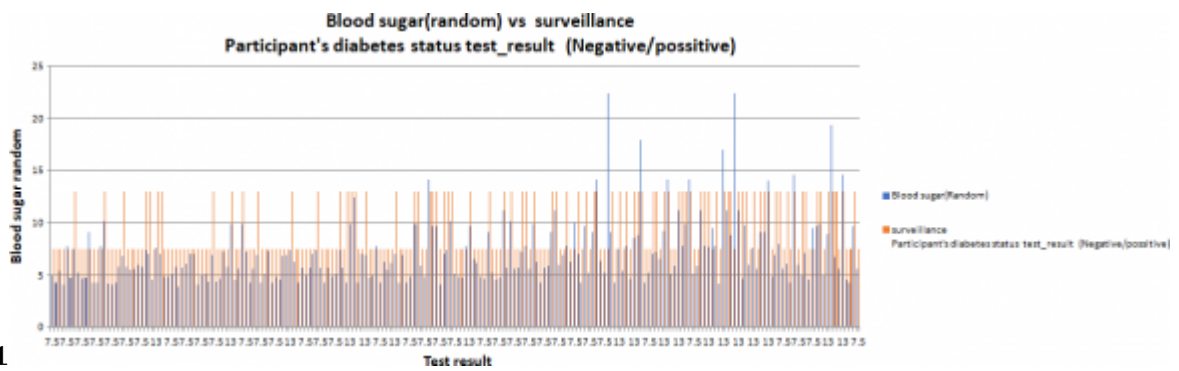


Figure 6: Fig. 4 . 1 :

4243

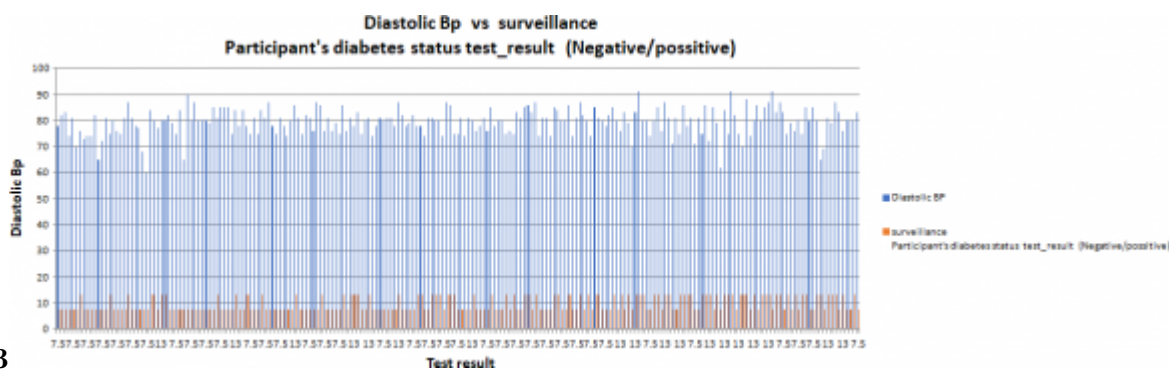
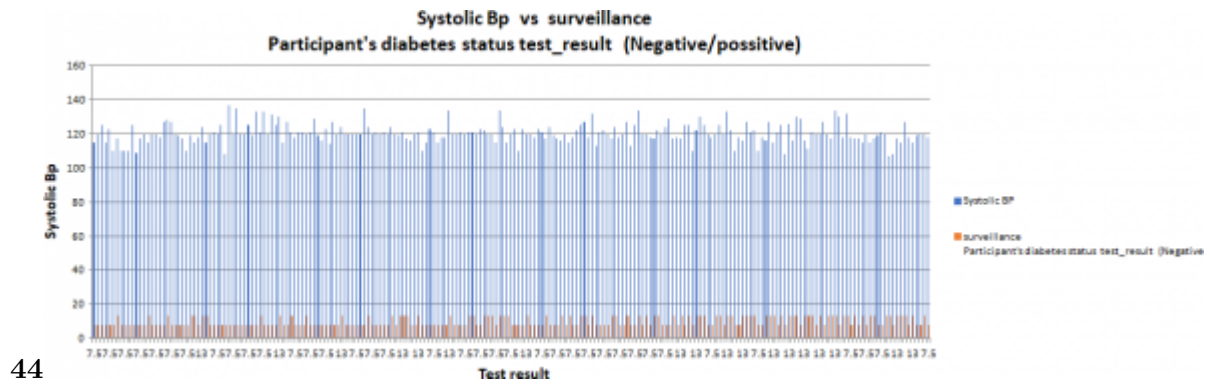
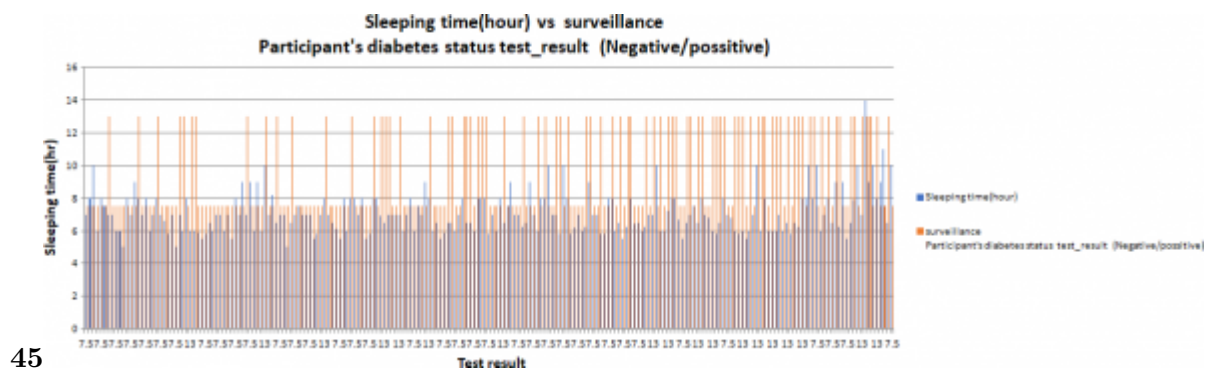


Figure 7: Fig. 4 . 2 : Fig. 4 . 3 :



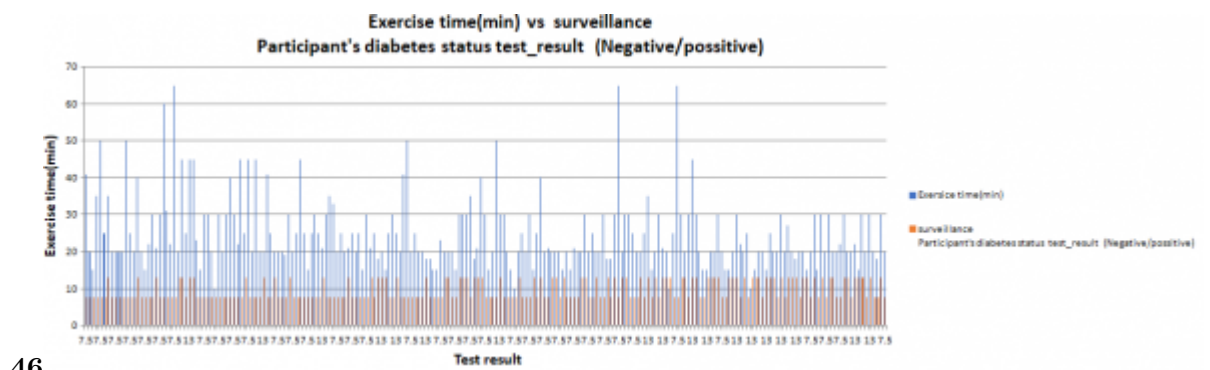
44

Figure 8: Fig. 4 . 4 :



45

Figure 9: Fig. 4 . 5 :



46

Figure 10: Fig. 4 . 6 :

$$47 \quad \frac{K*a*b*c*d*e*f}{g*h}$$

Figure 11: Fig. 4 . 7 :

$$48 \quad x = \frac{a * b * c * d * e * f}{2a}$$

Figure 12: Fig. 4 . 8 :

$$\frac{Age * BMI * Systolic Bp * Diastolic Bp * Blood sugar level(fasting period) * Blood sugar level(random period)}{Exercise Time + sleeping Time}$$

Figure 13:

$$\frac{\text{Occurrence} * \text{Exercise time} * \text{sleeping time}}{\text{Age} * \text{BMI} * \text{Systolic Bp} * \text{Diastolic Bp} * \text{Blood Sugar level (Fasting period)} * \text{Blood Sugar level (random period)}}$$

Figure 14:

$$\frac{100 * 16200 * 900}{1.41912 * 109 * 37 * 17331.6 * 11998.98 * (6 * 10^{-3}) * (8 * 10^{-3})}$$

Figure 15:

$$\frac{K * a * b * c * d * e * f}{g * h}$$

Figure 16:

1

Attribute Name	Lower bound	Upper bound
Age	1 year	123 years
BMI	10 kg/m ²	50 kg/m ²
Blood Sugar (Fasting)	3 mmol/L	10 mmol/L
Random Blood Sugar	5 mmol/L	30 mmol/L
Systolic Blood pressure	70 mmHg	190 mmHg

Figure 17: Table 1 A

```
If Random sugar level greater 0.007
Then Output 60 percent
Else output original result
2. Else if original result greater 30 and original result less than or equal to 50
If Random sugar level greater 0.007
Then Output 70 percent
Else output original result
3. Else if original result greater 50 and original result less than or equal to 80
then, Output original result
4. Else if original result greater 0 and original result less than or equal to 10 If Year
Random sugar level greater 0.007 Then, Output 55 percent 2021
Else output original result
5. Else if original result less than 0
If Random sugar level greater 0.007
then Output 51 percent
Else output 0.0001 percent
6. Else if original result greater 80 and original result less than or equal to 100
then, output original result
Else if original result greater 100
output 100 percent
else
Output "invalid input";
```

```
)
G
(
```

© 2021 Global Journals

Figure 18:

852 Exercise Time: In this graph, it represents the risk of diabetes occurrence was compared with the relational
853 attribute Exercise time .In this dataset what was used a primary data source for the research, the Exercise time
854 range was between the range of 10 min/day to 100 min /day of a different groups of male and female. Blue color
855 plotted line is representing the Exercise time/day (attribute). As per the information of dataset, Exercise time
856 started from the numerical value of 10 min/day and finished at the ending point of 100 min/day .In this graph,
857 Exercise time was compared with surveillance participants diabetes status test_result. The test result has two
858 different values i) Tested positive which is denoted as numerical value " 8.0 " (Yes/diabetes tested positive) to
859 make and plotting the intercepting graph flatters and to make it more flexible to compare differentiating points of
860 the graph , for ii) Tested Negative which is denoted as numerical value "3.50 " (False/diabetes tested Negative) to
861 make and plotting the intercepting graph flatters and to make it more flexible to compare differentiating points
862 of the graph. From the visual inspection of the graph, it is clear that Exercise time has a inversly proportional
863 relationship with the surveillance participants diabetes status test_result (negative/positive). Diabetes risk
864 occurrence is seriously /day to 60 min/day have the lowest risk probability .

865 From the analysis of the graph and previous studies, it is confirmed that people having the Exercise time <
866 20 min/day for a week have the higher risk of diabetes occurrences. Where k is a constant. By considering all
867 the medical datasheets and references it was confirmed that diabetes risk for certain factor has a certain upper
868 bound and risk doesn't increase exceeding that bound.

869 .1 Considering The worst case scenario

870 [Priyadarshini et al. ()] 'A Novel approach to Predict Diabetes Mellitus using Modified Extreme Learning
871 Machine, 1 edn'. Jrojalina Priyadarshini , Nilamadhab Dash , Rachita Mishra . *IEEE Xplorer: IEEE Xplorer*,
872 2014.

873 [Katzmarzyk et al. (2007)] 'Adiposity, physical fitness and incident diabetes: the physical activity longitudinal
874 study'. P T Katzmarzyk , C L Craig , L Gauvin . *Diabetologia* Mar. 2007. 50 (3) p. .

875 [Berber et al. (2001)] 'Anthropometric indexes in the prediction of type 2 diabetes mellitus, hypertension and
876 dyslipidaemia in a Mexican population'. A Berber , R Gómez-Santos , G Fanghänel , L Sánchez-Reyes . *Int.*
877 *J. Obes. Relat. Metab. Disord* Dec. 2001. 25 (12) p. .

878 [Rajesh and Sangeetha ()] 'Application of data mining methods and techniques for diabetes diagnosis'. K Rajesh
879 , V Sangeetha . *International Journal of Engineering and Innovative Technology (IJEIT)* 2012. 2 (3) p. .

880 [Adidela et al. ()] 'Application of fuzzy ID3 to predict diabetes'. D R Adidela , D G Lavanya , S G Jaya , A R
881 Allam . *Intr Jrnl Adv Comp Math Sci* 2012. 3 (4) p. .

882 [Feng et al. (2012)] 'BMI is strongly associated with hypertension, and waist circumference is strongly associated
883 with type 2 diabetes and dyslipidemia, in northern Chinese adults'. R N Feng , C Zhao , C Wang , Y C Niu
884 , K Li , F C Guo , S T Li , C H Sun , Y Li . *J. Epidemiol* May 2012. 22 (4) p. .

885 [Ara et al. ()] 'Case Study :Integrating IoT, Streaming Analytics and Machine Learning to improve Intelligent
886 Diabetes Management System, 1 edn'. Affreen Ara , Aftab Dr , Ara . *International Conference on Energy,*
887 *Communication, Data Analytics and Soft Computing*, 2017. IEEE. (ICECDS-2017)

888 [Cash ()] Jill Cash . *Family Practice Guidelines*, 2014. Springer. 9780826168757 p. 396. (3rd ed.)

889 [T ()] 'Control and complications Trial Research Group. The effect of intensive treatment of diabetes on the
890 development and progression of long-term complications in insulin independent diabetes mellitus'. T . *N Engl*
891 *J Med* 1993.

892 [Afrandp et al. ()] 'Design and implementation of an expert clinical system for diabetes diagnosis'. Afrandp , N
893 M Yazdani , H Moetamedzadeh , Naderif , M S Panahi . *Global Jrnl of Sci, Engg* 2322- 2441. 2012. p. . (Tech)

894 [Diabetes Fact sheet N°312 (2013)] *Diabetes Fact sheet N°312*, October 2013. 25 March 2014.

895 [Bum Ju Lee and Jong Yeol Kim (ed.) ()] *Identification of Type 2 Diabetes Risk Factors using Pheno Type*
896 *Consisting of Anthropometry and Triglycerides based on Machine Learning, 1 edn*, IEEE xplorer: IEEE
897 xplorer. Bum Ju Lee and Jong Yeol Kim (ed.) 2014.

898 [Snijder et al. (2004)] 'Independent and opposite associations of waist and hip circumferences with diabetes,
899 hypertension and dyslipidemia: the AusDiab Study'. M B Snijder , P Z Zimmet , M Visser , J M Dekker , J
900 C Seidell , J E Shaw . *Int. J. Obes. Relat. Metab. Disord* Mar. 2004. 28 (3) p. .

901 [Patel ()] 'Intensive blood glucose control and vascular outcomes in patients with type 2 diabetes'. A Patel . *The*
902 *New England journal of medicine* 2008. 358 p. .

903 [Suzuki et al. ()] 'Mixture of expert 3D massivetraining ANNs for reduction of multiple types of false positives
904 in CAD for detection of polyps in CT colonography'. K Suzuki , H Yoshida , J Nappi , S G Armato , A H
905 Dachman . *Med. Phys* 2008. 35 (2) p. .

906 [Webb and Zheng (2004)] 'Multistrategy ensemble learning: Reducing error by combining ensemble learning
907 techniques'. G I Webb , Z Zheng . *IEEE Transactions on Knowledge and Data Engineering* Aug. 2004. 16 (8)
908 p. .

- 909 [Webb and Zheng (2004)] ‘Multistrategy ensemble learning: Reducing error by combining ensemble learning
910 techniques’. G I Webb , Z Zheng . *IEEE Transactions on Knowledge and Data Engineering* Aug. 2004. 16 (8)
911 p. .
- 912 [Kumar and Pranavi ()] *Performance Analysis of Machine Learning Algorithms on Diabetes Dataset using Big
913 Data Analytics*, P Kumar , S Pranavi . 2017. (IEEE xplorer)
- 914 [Varshney ()] *Pervasive Healthcare Computing: EMR/EHR, Wireless and Health Monitoring*, U Varshney . 2009.
- 915 [Anand and Shakti (2015)] ‘PREDICTION OF DIABETES BASED ON PERSONAL LIFESTYLE INDICA-
916 TORS, 1 edn’. Ayush Anand , Divya Shakti . *1st International Conference on Next Generation Computing
917 Technologies (NGCT-2015)*, (Dehradun, India) September 2015. 2015.
- 918 [Saravanakumar and Sampath ()] ‘Predictive Methodology for Diabetic Data Analysis in Big Data’. Eswari T
919 Saravanakumar , P Sampath . *Science direct* 2015. 50 p. .
- 920 [Kumar and Srivastava (2014)] ‘Some observations on the performance of segmentation algorithms for micro-
921 scopic biopsy images’. R Kumar , R Srivastava . *Proceedings of the International Conference on modeling
922 and Simulation of Diffusive Processes and Applications (ICMSDPA '14)*, (the International Conference on
923 modeling and Simulation of Diffusive Processes and Applications (ICMSDPA '14)Varanasi, India) October
924 2014. p. . Department of Mathematics, Banaras Hindu University
- 925 [Lear et al. (2002)] ‘The relationship between waist circumference and metabolic risk factors: Cohorts of
926 European and Chinese descent’. S A Lear , M M Chen , J J Frohlich , C L Birmingham . *Metabolism*
927 Nov. 2002. 51 (11) p. .
- 928 [Misra et al. (2006)] ‘Waist circumference cutoff points and action levels for Asian Indians for identification of
929 abdominal obesity’. N K Misra , R Vikram , R M Gupta , J S Pandey , V P Wasir , Gupta . *Int. J. Obes.
930 (Lond)* Jan. 2006. 30 (1) p. .
- 931 [Xu et al. (2013)] ‘Waist-to-height ratio is the best indicator for undiagnosed type 2 diabetes’. Z Xu , X Qi , A
932 K Dahl , W Xu . *Diabet. Med* Jun. 2013. 30 (6) p. .