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A Review on Type II Diabetes Prediction Using Machine Learning Techniques

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ABSTRACT:

Diabetes mellitus is one of the major health problems in the world. Various research works have attempted in predicting diabetes mellitus in general and type-2 diabetes using various machine learning techniques such as Artificial Neural Networks, Support Vector Machine, Random Forest, and Decision Tree. The research work that was reviewed suggests that, using an ensemble of machine learning models provides more accuracy in predicting diabetes. Due to the high accuracies provided by Random Forest and Neural Network models in the analysed studies, we suggest that using Random Forest and Neural Network combined machine learning models will be able to give high prediction accuracy rates in future research. This study contributes to the literature by providing insights on which techniques can be most accurate in developing a machine learning model to predict diabetes mellitus, which can be embedded into Clinical Decision Support Systems. This review paper discusses various approaches researchers have taken in predicting diabetes mellitus and their results. Therefore, researchers could dive deep into the research that is currently available and their progress by comparing the results.

Keywords: **Diabetes mellitus, type-2 diabetes, prediction, machine learning, early detection**

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1 INTRODUCTION

Machine Learning (ML), a branch of Artificial Intelligence (AI), gives machines the ability to perform intelligent tasks. Among them, predicting the future by analyzing the past data and identifying patterns in them is a prominent feature. Diabetes is one of the most common diseases among many adults today. It is rising among teenagers and children as well. Therefore, the prediction of diabetes before actually diagnosing it later can be advantageous in the early prevention of the disease.

This review paper focuses on various studies conducted on predicting diabetes mellitus, type-2 to be specific, using various ML techniques. This literature review compares and contrasts different ML techniques used in the research that have been filtered out to be analysed, and discusses the most suitable techniques among them to be used in Clinical Decision Support Systems (CDSS) and other Information Systems to support doctors in predicting Type-2 Diabetes (T2DM) successfully among their patients.

2 BACKGROUND

2.1 DIABETES MELLITUS

Diabetes mellitus or hyperglycemia can be described as a metabolic disorder of the pancreas. Diabetes is the state where there is a high glucose level in the bloodstream. Five types of diabetes can be diagnosed in a patient, namely prediabetes, Type 1 Diabetes Mellitus (T1DM), Type 2 Diabetes Mellitus (T2DM), Latent Autoimmune Diabetes - LADA in adults (*Prediabetes Can Be Associated with Both Type 1 and Type 2 Diabetes*, n.d.) and gestational diabetes. Prediabetes is the initial stage of a diabetic patient. If not treated well, prediabetes can be developed into T1DM or T2DM, but if treated well, risk of diabetes can be reduced or even prevented (*Prediabetes Can Be Associated with Both Type 1* *and Type 2 Diabetes*, n.d.).

T1DM occurs when the pancreas fails to produce insulin, a hormone that regulates blood glucose levels by binding to receptor cells in target organs, allowing them to absorb glucose. Glucose, derived from carbohydrates, reacts with oxygen to supply energy to the body's organs. T1DM results from an autoimmune response where the immune system mistakenly attacks the pancreatic β cells, leading to insufficient insulin production. Without enough insulin, glucose cannot be properly absorbed by the organs, causing elevated blood glucose levels. In contrast, T2DM is characterized by either a malfunction in insulin receptor binding or defects in cellular signaling, rendering target cells unresponsive to insulin (*Diabetes Type 1 and Type 2, Animation.*, n.d.). T1DM is mostly diagnosed in younger people while adults are most prone to be diagnosed with T2DM.

LADA is diagnosed mostly in adults after 30 years of age. These patients show symptoms of both T1DM and T2DM. Some experts believe that LADA is the slowly developing kind of T1DM because the patients have antibodies that are against the β cells in their pancreas (*Prediabetes Can Be Associated with Both Type 1 and Type 2 Diabetes*, n.d.). Gestational diabetes is a form of diabetes that occurs during pregnancy. While it often resolves after childbirth, in some cases it can persist or progress into other forms of diabetes, such as Type 2 Diabetes, becoming a long-term condition for the patient.

2.2 MANUAL METHOD OF DIAGNOSING DIABETES

Diabetes mellitus, whether Type 1 or Type 2, is typically diagnosed in clinical settings through blood tests that measure blood glucose levels. The fasting blood sugar test is the most common diagnostic method, though patients can also perform random blood sugar tests at home using glucometers. In a fasting blood sugar test, levels between 100 and 125 mg/dL indicate prediabetes, while levels of 126 mg/dL or higher suggest diabetes. For random blood sugar tests, a reading of 200 mg/dL or higher is indicative of diabetes, regardless of when the patient last ate.

On the other hand, oral glucose tolerance tests are conducted mostly on pregnant women where a sugary liquid is consumed at the doctor's and the blood sugar level is measured periodically for the next two hours, which is an essential task to diagnose gestational diabetes. However, to diagnose T2DM specifically, a special test called the glycated haemoglobin (HbA1C or simply A1C) is conducted and a result between 5.7-6.4% is considered prediabetes, while an A1C level of 6.5% or higher is considered diabetes (*Type 2 Diabetes - Diagnosis and Treatment - Mayo Clinic*, n.d.).

3 SIGNIFICANCE OF PREDICTING DIABETES

Most prediabetic patients are later diagnosed with T2DM, which is the most common type of diabetes among adults. Even though diabetes can be delayed or even prevented in patients if identified correctly during the prediabetes stage, prediction of the disease is still at the research level. According to the National Diabetes Prevention Program of the United States, by changes in the diet and by weight loss through exercising, prediabetes can be prevented as much as 58% and up to 71% if the patient is over the age of 60 (CDC, 2020).

In 2016, the U.S. Centers for Disease Control and Prevention (CDC) reported that 24.8 out of every 100,000 individuals died from diabetes-related causes. While the CDC did not provide specific data on the impact of diabetes on life expectancy, a 2012 Canadian study offers insights into this issue. The study found that, at age 55, diabetes reduces life expectancy by an average of 6 years for women and 5 years for men (*Type 2 Diabetes and Life Expectancy*, 2022). When considering these mortality rates, it is without a doubt important to predict diabetes rather than trying to control it after diagnosing. Therefore, in this review paper, some of the remarkable studies conducted are analysed to evaluate the best ML technique in predicting T2DM.

4 METHODOLOGY

The research articles were identified to be reviewed following a bibliometric analysis, being inspired from the PRISMA Flow Diagrams, shortened for Preferred Reporting Items for Systematic Reviews and Meta-Analysis (*PRISMA Flow Diagrams - YouTube*, 2017). After eliminating any duplicate studies, 25 research papers were identified. Following this, each paper underwent either an abstract review or a full-text examination, leading to the exclusion of 11 studies. This process left 14 significant research papers for in-depth analysis. Figure 1 provides a visual representation of the selection process used to identify the relevant research for this review paper.

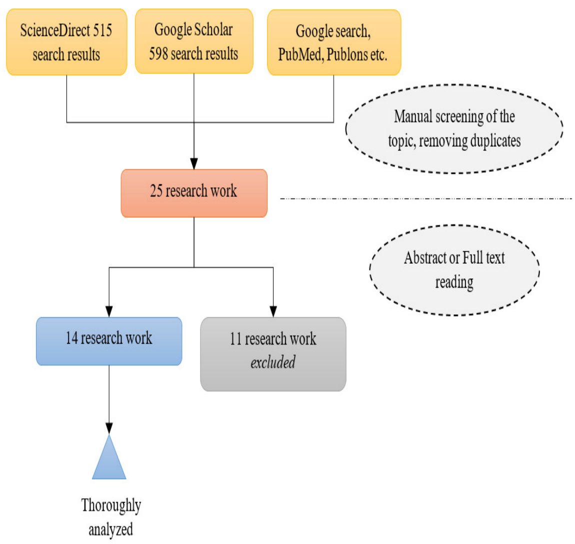

Figure 1: *Identification of Suitable Research work*

5 RESULTS AND DISCUSSION

When taking an overview of the selected research work, the use of different artificial intelligence techniques for the prediction purposes can be identified such as fuzzy logic, support vector machines (SVM), neural networks (NN), random forests (RF), and decision trees (DT). Also data mining techniques such as k-means clustering and associate rule mining have also been used parallel to ML techniques. When visualizing the density of the keywords (Refer Figure 2 - generated from the scientific visualization tool VOSviewer (*VOSviewer - Visualizing Scientific Landscapes*, n.d.)), it makes it clear that most researches have used support vector machines, neural networks, random forests, and decision trees to predict diabetes in their work.

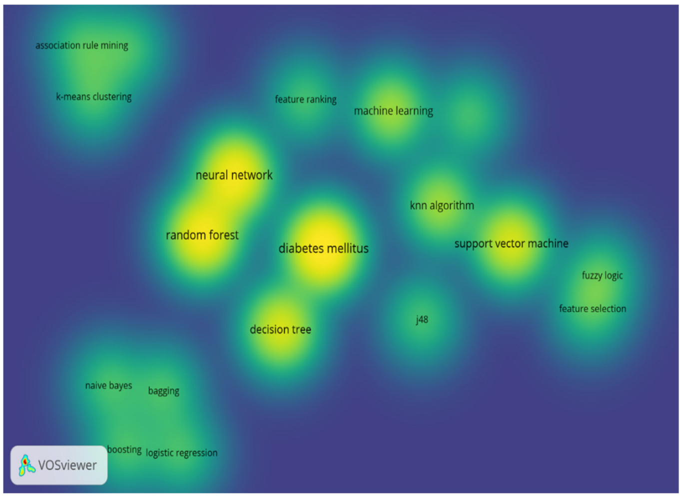

Figure 2: *Density visualization of the keywords*

When considering the 14 research works selected, the researchers have used different techniques and datasets. Among the datasets they have used, it can be seen that many of them have used the Pima Indian Diabetes (PID) dataset, which can be used as a common factor to compare and contrast the research results in 10 out of 14 research works cited in this review paper.

Table 1: *Summarization of Research work cited*

No	Research title	Dataset(s) used	Techniques used	Diabetes (type) evaluated
1	Type 2 Diabetes Risk Forecasting from EMR Data using Machine Learning (Mani et al., 2012)	EMR of Vanderbilt University Medical Center	Gaussian NB, LR, kNN, CART, RF, and SVMs	T2DM
2	An Improved Data Mining Model to Predict the Occurrence of Type-2 Diabetes using Neural Network (Priya & Rajalaxmi, 2012)	PID	Data Mining technique C4.5 for the initial classification and is improved by NN	

3	Diabetes Prediction: A Deep Learning Approach (Ayon & Islam, n.d.)	PID	Deep learning	
4	Predicting Diabetes Mellitus With Machine Learning Techniques (Zou et al., 2018)	hospital examination data in Luzhou, China, PID	RF, Decision Tree, NN, mRMR (Zou et al., 2018)	Diabetes mellitus
5	An improved early detection method of type-2 diabetes mellitus using multiple classifier system (Zhu et al., 2015)	PID, Indonesian Patients (IP)	NN, LR, SVM, C4.5, NB, MFWC (Zhu et al., 2015)	T2DM
6	Prediction of Diabetes Using Artificial Neural Network Approach (Rahimloo & Jafarian, 2016)	PID	NN	Diabetes mellitus
7	The virtual doctor: An interactive clinical-decision-support system based on deep learning for non-invasive prediction of diabetes (Spänig et al., 2019)	Heinz-Nixdorf-Recall Study (HNR) (Spänig et al., 2019) data (4814 participants)	Deep Learning, DNN, SVM	T2DM
8	Diabetes Prediction Using	PID	DT, NN, NB, SVM	Diabetes Mellitus

	Different Machine Learning Approaches (Sonar & JayaMalini, 2019)			
9	Comparison of Classifiers for the Risk of Diabetes Prediction (Nai-arun & Moungmai, 2015)	26 Primary Care Units (PCU) in Sawanprachak Regional Hospital during 2012 – 2013 (30,122 people)	13 models including bagging and boosting, DT, NN, LR, NB	
10	A model for early prediction of diabetes (Mahboob Alam et al., 2019)	PID	NN, RF, k-means	
11	Early Detection of Diabetes Mellitus using Feature Selection and Fuzzy Support Vector Machine (Lukmanto et al., 2019)	PID	Fuzzy SVM	
12	Predictive modelling and analytics for diabetes using a machine learning approach (Kaur & Kumari, 2018)	PID	5 predictive models Linear SVM, radial basis function (RBF), kernel SVM, kNN, NN and multifactor dimensionality reduction (MDR)	
13	Performance Analysis of Classifier Models to Predict	PID	DT, J48, kNN, RF, SVM in 2 separate situations (before data	

	Diabetes Mellitus (Kandhasamy & Balamurali, 2015)		prepossessing and after)	
14	Predicting the onset of type 2 diabetes using wide and deep learning with electronic health records (Nguyen et al., 2019)	EHR dataset from the United States released by Practice Fusion in 2012 for a data science competition (Nguyen et al., 2019)	Wide and deep learning framework	T2DM

As reported by Kaggle Inc., a major platform for publicly available datasets and code, the Pima Indians Diabetes (PID) dataset originates from the National Institute of Diabetes and Digestive and Kidney Diseases. It was later published in the University of California Irvine (UCI) Machine Learning Repository. This dataset comprises 768 entries with 9 variables. All the individuals included in the dataset are women of at least 21 years of age, and they are of Pima Indian heritage (*Pima Indians Diabetes Database*, n.d.).

Table 1 gives an overall view of the 14 research work analysed in this review paper with accordance to the dataset(s), techniques the researchers have used while indicating the diabetes type they have tried predicting in their work. It can be seen that Gaussian Naïve Bayes (NB), Logistic Regression (LR), k-nearest neighbour (kNN), and Classification and Regression Trees (CART) have also been used in the predictive models the researchers have come up with.

In their research, Subramani Mani et al. utilized Electronic Medical Records (EMR) from Vanderbilt University Medical Center, organizing the data into three distinct datasets labeled D365, D180, and D0, based on cut-off days of 365, 180, and 0, respectively. The D180 dataset refers to patients whose data was available in the EMR 180 days prior to their Type 2 Diabetes (T2DM) diagnosis. The researchers applied several machine learning techniques, including Gaussian NB, LR, kNN, CART, RF, and SVMs, to test the datasets. Their findings indicated that RF outperformed the other methods overall. However, they noted that while RF provided superior results, its outputs were not easily interpretable for medical professionals in clinical settings. In contrast, the results from CART were found to be more comprehensible for human interpretation. (Mani et al., 2012). However, their objective of this research is to identify that the EMR is feasible enough to forecast the risk of diabetes before 365 and 180 days and they have achieved in doing so.

S. Priya et al. in their study have used the PID dataset and have used NN to improve the classification model made using data mining. They have mentioned that the model only when using the C4.5 classifier, data mining model was able to give a 91% accuracy rate, while when using NN to improve the data mining model, it was able to give a success rate of 96%-98%. They have also used Kappa statistics, which serves as an agreement between two different qualitative observations, to compare the two models. And the kappa statistics show that the NN model has performed better with a success rate of 0.953 while C4.5 classifier has only given a rate of 0.8249 (Priya & Rajalaxmi, 2012).

Safial et al. have proposed a deep neural network (DNN) on the PID dataset, where they have been able to get an accuracy of 98.35%, among the other ML techniques they have used. Quan Zou et al. have used both the PID dataset and also hospital examination data in Luzhou, China. They have tested the data for five times and have stated that the results they have presented in the paper are the average of the five experiments. They have used Principal Component Analysis (PCA) and minimum redundancy maximum relevance (mRMR) to reduce the dimensionality (Zou et al., 2018). Among the machine learning models they used - RF, NN, and data mining technique J48, the RF has given the best performance without blood glucose. Nevertheless, they have found out that using all features for the prediction still has a better result. Moreover, it is said that only using blood glucose as a feature to predict diabetes is not a good decision, especially with the neural network as a classifier. Their results suggest that using mRMR, an accuracy of 77.21% was obtained on the PID dataset, while the accuracy of 80.84% was obtained on the Luzhou dataset.

On the other hand, Jia Zhu et al. have used multiple classifier systems (MCS) with a dynamic weighted voting scheme called multiple factors weighted combination for classifiers' decision combination (MFWC), to improve the accuracy of the detection of T2DM on the PID dataset and as well as an Indonesian dataset (Zhu et al., 2015). They have noticed that combined methods have performed better than using individual classifiers to predict T2DM. It is also noted by Jia Zhu et al. that MFWC has a slightly larger training time compared to other models and that it takes around 0.2 seconds to identify whether a person is a T2DM patient or not, which is still fast enough for a real application. The researchers have validated their MFWC with other complex diseases as well and have observed that this combination remains at the top position on identifying those diseases.

Suyash et al. in their research of predicting diabetes using the artificial neural network approach have also used the PID dataset. They indicate that the NN was able to provide a 92% accuracy rate on the sample test data and mentions that their model will be able to perform even better if exposed to much data in the future.

Sebastian et al. have used SVM and DL to develop a model to predict T2DM and have applied that model into an AI-based Clinical Decision Support System (CDSS) which they call as a virtual doctor (Spänig et al., 2019), to provide a solution to the exact problem that is brought forward in this review paper. The CDSS consists of a patient cube, which the patient has to go into for the system to measure the patient's weight and height with the use of weight and ultrasonic sensors. The CDSS is powered with speech recognition, which is used to ask questions from the patient to get a general idea about the patient's lifestyle. Among the various questions posed by the system, the patient's age, gender and anamnesis are identified, from which the virtual doctor can predict whether the patient is prone to diabetes or not. The data used for their prediction model was sourced from the Heinz-Nixdorf-Recall (HNR) study. Among the machine learning techniques tested, DNN outperformed SVM in predicting T2DM, leading the researchers to implement the prediction model using DNN. When the prediction probability falls between 30-70%, an HbA1C test is recommended by a virtual doctor (Spänig et al., 2019). The researchers noted that the DNN model, even when trained without HbA1C test results, outperformed the SVM based on the Area Under the Curve (AUC), which was a key factor in selecting DNN for the initial prediction.

AUC is a measure used in classification analysis to evaluate which model best predicts the classes. An example of its application is ROC curves (Receiver Operator Characteristic) where the true positive rates are plotted against false positive rates (*Classification - What Does AUC Stand for and What Is It?*, n.d.). As Sebestian et al. describe, there can be cities where the population is not inspectable by the medical personnel in that area. Therefore, in such situations, it is always better if an AI-based virtual doctor can take the real medical person's place.

Sonar et al. have also used the PID dataset in predicting diabetes mellitus using the techniques DT, NB and SVM. They have provided that the highest precision is given by the DT which is 85%. Nai-arun et al. on the other hand have conducted a comparison between various classifiers for the prediction of diabetes. They have collected the data from 26 Primary Care Units (PCU) in Sawanpracharak Regional Hospital during 2012 – 2013, containing 30122 records. They have used bagging and boosting algorithms on DT, NN, LR and NB. Boosting algorithm is used to reduce an error of a weak classifier while bagging algorithm was introduced to avoid overfitting and reduce the variance of the predicting model (Nai-arun & Moungmai, 2015). They have also created a web application using the model, where they have used RF for the prediction because RF has the highest ROC curve value of 85.558% as accuracy. This web application lets the patients log into it and enter their details in order to view the prediction regarding them, which is another application where the manual process of diagnosing diabetes can be replaced by the automated process.

Mahboob et al. have also used the PID dataset to predict diabetes using NN, RF and k-means clustering, which is a data mining technique. In their research, the NN has achieved the best accuracy rate of 75.7%. Lukmanto et al. on the other hand have used the PID dataset and have used an advanced version of SVM to do the prediction. They have used fuzzy logic in combination with SVM to come up with a fuzzy SVM model which strengthens and optimizers the traditional SVM classifier. Fuzzy SVM can be used for classification analysis and it is aimed at finding the most optimal hyperplane (Lukmanto et al., 2019). The results show an accuracy of 89.02% when using the fuzzy SVM model.

Kaur and Kumari in their research work (Kaur & Kumari, 2018) have proposed 5 predictive models using linear SVM, RBF, kernel SVM, kNN, NN and MDR. They have used these models to predict diabetes mellitus in the PID dataset. The best accuracy was given by SVM, a rate of 89% while giving a precision of 88%. Another study by Kandhasamy and Balamurali have also used the PID dataset and their predictions are done using DT, kNN, RF and SVM. They have also used bagging to enhance the prediction models. They have compared their models in two different situations as before pre-processing and after pre-processing. They have concluded that before pre-processing, the DT with J48 classifier has achieved the highest accuracy while after pre-processing, kNN where k=1 and RF have provided 100% accuracy. Therefore, it can be seen that, after removing noisy data from the dataset, the models provide good results for the predictions (Kandhasamy & Balamurali, 2015).

Nguyen et al.'s research also used electronic health records (EHR) that was used by Practice Fusion, the United States in 2012 for a data science competition. This dataset contains records of 9948 patients with 1904 diagnosed with T2DM. They have developed an algorithm for the prediction of diabetes onset based on the wide and deep learning framework (Nguyen et al., 2019). The researchers applied the Synthetic Minority Oversampling Technique (SMOTE) to enhance the dataset's performance. They observed that their ensemble of classifiers, combining RF and NB, achieved an accuracy rate of 84.28% and a specificity rate of 96.85% after being improved with SMOTE.

When considering all the above-cited research work, it can be seen that the accuracy results obtained differs not only because of the use of different classifiers but also due to the datasets that have been used. Therefore, to compare the results brought forward in these different research work, it is easier to compare models that have used the same dataset, in this case, the PID dataset. Table 2 shows the results obtained in the 14 research works in a summarized and comprehensible manner.

Table 2: *Best performed models with their accuracies*

Research No	Accuracy on PID	Accuracy on other datasets
1		Over 70% - using RF on EMR of Vanderbilt University Medical Center (Mani et al., 2012)
2	96-98% - using NN	
3	98.35% - using DL	
4	77.21% using mRMR (Zou et al., 2018)	80.84% - using RF on hospital examination data in Luzhou, China
5	Almost 95% - using MFWC (Zhu et al., 2015)	97-98% using MFWC (Zhu et al., 2015) - on IP dataset
6	92% - using NN	
7		DNN – an AUC of 0.703 on HNR(Spänig et al., 2019)
8	85% - using DT	
9		85.558% - using RF with the highest ROC curve on data from 26 PCU in Sawanpracharak Regional Hospital (Nai-arun & Moungmai, 2015)
10	75.7% - using NN	
11	89.02% using Fuzzy SVM	
12	89% using SVM, with a 88% precision	
13	Before preprocessing, J48 has given 73.82% accuracy. After preprocessing, kNN (when k=1) and RF have given 100% accuracy.	
14		The ensemble of RF and NB has given 84.28% accuracy on EHR dataset from the United States released by Practice Fusion in 2012 for a data science competition (Nguyen et al., 2019)

When considering Table 1 and Table 2, it can be seen that 10 out of the 14 research works cited have used the PID dataset for diabetes prediction purposes. And 2 out of those 10 research work have used the PID dataset to predict T2DM, while the other 8 research work predicts diabetes mellitus in general. When considering all the research work cited, it can be seen that there are a total of 5 research works that have the hypothesis of predicting T2DM using ML techniques, and other 9 are predicting diabetes mellitus.

Conversely, when analyzing the PID dataset, it is important to note that it includes only female patients aged 21 and older. This limitation raises concerns about the dataset's generalizability for predicting diabetes across all patients, regardless of gender, and specifically for predicting T2DM. This may explain why only 2 out of the 5 studies utilized the PID dataset for T2DM prediction, while the remaining 3 studies opted for their custom datasets, which contained a larger number of records for predictive analysis.

It can be seen that the research work done to predict T2DM specifically using ML techniques is scarce, which is why a concrete conclusion cannot be given by this review paper as to what method would be the best to be used for the prediction of T2DM. Therefore, when considering all the 14 research papers, it can be seen that RF and NN have the best overall performance in predicting diabetes, while there are 2 out of 14 research works cited that have obtained better results using SVM and 1 out of 14 have been successful in using DT. It can also be seen from Table 2 that RF has been successful in predicting well when it comes to custom datasets, other than the PID dataset. When analysing deeper on the research that predicts T2DM, it can be seen that either NN or DNN have performed best. The difference between NN and deep learning lies with the depth of the model that was used (*About Artificial Intelligence, Neural Networks & Deep Learning*, 2017; Nielsen, 2015). The MFWC has also been able to make a considerably good prediction. Among the researches that have combined many models to obtain better results, the MFWC has been more successful than the ensemble of RF and NB that has only obtained an accuracy rate of 84.28%. From the research work reviewed in this paper, it can also be identified that models give better results when the dataset is having less noisy data.

The derivation I have obtained earlier, from analysing the data extracted from the full-text read of the research work indicates that RF, NN, SVM and DT have given the best results. RF and NN are the better ML techniques for T2DM prediction when considering the above 14 research work, each reserving 5 out of 14 research work with best results.

5 CONCLUSION

Diabetes mellitus is a non-commutable disease with a very high affecting rate. This review paper's objective was to review the existing research works that were conducted on predicting T2DM with the use of various machine learning techniques. Although this particular specialized area is scarce, among the research work cited, it can be seen that random forest and neural networks have provided the best prediction accuracies. It should also be noted that when comparing the results of the work, the accuracies tend to depend highly on the dataset used for the prediction. Even though many pieces of research have used the PID dataset since it is freely available at UCI machine learning repository and Kaggle, there is a doubt as to how appropriate it is to use this particular dataset to predict T2DM or diabetes among general patients, where it contains only data of female patients.

Therefore, these suggestions can be made after analysing the research work. It is highly recommended to use a custom dataset for the future T2DM predictions that contain details of both female and male patients. If a person is predicting diabetes mellitus in general, a dataset containing patient data from all age groups is acceptable, while if the research work is focused on predicting T2DM, as mentioned in this review paper, it is acceptable for the researchers to use a dataset that contains data of more adult patients, as T2DM is mostly present in adults and less in children.

Many research-work that have done diabetes and T2DM prediction using multiple machine learning models have succeeded in their work, and also studies that have used RF and NN have also succeeded in their prediction with high accuracy rates. Therefore, it can be suggested that using RF and NN combined machine learning models will be able to give high prediction accuracy rates in future research. Futhermore, having these two machine learning techniques integrated with a CDSS will be an added advantage for clinical facilities in predicting T2DM.

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