International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An IOT Based Smart Health Care System using Deep Learning Technique for Diabetes Prediction

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Submitted: 05/02/2024 **Revised**: 13/03/2024 **Accepted**: 19/03/2024

Abstract: Diabetes is a chronic disorder brought on by a malfunction in the metabolism of carbohydrates, and it has emerged as a major global health issue. But in addition to a review of important symptoms, several time-consuming tests are performed to identify diabetes. Healthcare systems provide specialized services in a variety of fields to help patients integrate into their regular daily activities. The primary goal of this work is to use the Transformer neural network to increase the accuracy of diabetes prediction using an IoT-based healthcare system. The outcomes on the Pima Indian dataset (PID) demonstrate the efficacy of the deep learning approach with prediction accuracy scores of 98.54%, sensitivity levels of 95.36%, specificity levels of 94.52%, and F1 score values of 92.58% for diabetes prediction.

Keywords: Diabetes, IoT health care system, deep learning, accuracy

1. Introduction

Diabetes is a widespread chronic condition that seriously endangers people's health. When blood glucose levels are greater than normal, whether due to increased insulin production or other biological factors, diabetes can be diagnosed. 422 million people worldwide, predominantly in low- or middle-income countries, have diabetes, according to the World Health Organization. Additionally, this might be expanded to 490 billion by the year 2030. However, diabetes is common in many nations, including Canada, China, and India, among others. Since India has a population of over 100 million people, there is actually 40 million diabetes there [10].

According to the pathological investigation's findings, diabetes has several pathological causes, and it may be divided into three major groups. Type 1 diabetes (T1D) is brought on by insufficient insulin production from the pancreas; Type 2 diabetes(T2D) is brought on by inefficient insulin use from the body; and gestational diabetes, if not appropriately managed, poses serious health hazards. Normally known as primary diabetes, T1D is caused by damage to the insulin-secreting cells in the pancreas, which prevents the body from producing enough insulin to reduce blood sugar levels on time.

T2D is known as non-insulin-dependent diabetes since it does not utilize the body's insulin effectively. Generally, because of insulin resistance or issues with insulin production, etc., which results in high blood sugar. A pregnant woman experiences temporary gestational diabetes, which goes away after giving birth. They run the chance of experiencing various complications both during pregnancy and delivery. Before becoming pregnant, this can be avoided by healthy exercise and weight management.

Increased appetite, thirst, and frequency of urination are some signs of diabetes, which is directly indicated by high blood sugar. It takes at least 200 mg/dL of plasma glucose over two hours after a load to diagnose diabetes and some research on the subject advocates for prompt call identification. Patients with diabetes typically need ongoing care; otherwise, serious, sometimes fatal complications may arise. An important factor in curing diabetes is quickly and accurately identifying it in the early stages [7].

Early identification and symptomatic management of pre-diabetic individuals are essential to their healthy life and well-being. An intelligent medical diagnostic system based on symptoms, indicators, laboratory tests, and observations will make it simpler to identify illnesses and take preventative measures against them. Additionally, AI has been used in a variety of intriguing ways to detect diseases in medical diagnosis systems [8].

However, several time-consuming tests are performed, coupled with an analysis of key indications, to identify diabetes. Therefore, to address the issue and cut costs, machine learning algorithms are employed to identify and diagnose diseases. Additionally, selections made with the aid of machine learning technologies were precise and essential. A human would find it difficult and occasionally

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impossible to manage the vast volume of data. As a result, deep learning is quickly gaining popularity and is strikingly comparable to how the human mind functions. It offers a large variety of data formats and solves the selectivity-invariance issue well. Deep learning technologies are commonly applied to the field of medical prognosis [11]. It can easily comprehend difficult problems and process enormous amounts of data. It has made significant strides in sectors like speech recognition and computer vision. Numerous studies demonstrated that deep learning techniques outperform traditional ones in terms of effectiveness, classification error rates, and noise robustness.

The main contribution of our proposed method is listed:

- To facilitate better diagnostic decision-making, create an automated remote monitoring system that combines patient vital information from smartphones.
- Using a transformer encoder to classify data that is normal and diabetic and to improve diabetes prediction.
- To improve detection by reducing false positives in comparison to other methods currently in use and to achieve high accuracy in diabetes detection by using Pima Indian dataset.

2. Literature survey

Madan et al. [9] used the publicly accessible PIMA Indian diabetes database to create a hybrid deep learning-based system for real-time monitoring, diagnosis, and forecasting of diabetes mellitus type-2. Four new insights are provided by this study. They carried out a comparative analysis of various deep learning models first. To detect (and forecast) Type 2 diabetes, authors then proposed CNN-Bi-LSTM, a merging of two models based on experimental results. These findings demonstrated that CNN-Bi-LSTM outperformed other cutting-edge algorithms by 1.1% with accuracy (98%), sensitivity (97%), and specificity (98%) when compared to other deep learning techniques. The suggested approach enables physicians to analyze vital sign numbers in real-time and gather thorough patient information through real-time monitoring.

An end-to-end remote monitoring system for automated diabetes risk prediction and management using cell phones, wearables, and personal health devices was presented by Ramesh *et al.*[22]. Using the PIMA Indian Diabetes Database, a support vector machine was created after feature scaling, imputation, selection, and augmentation. Accuracy, sensitivity, and specificity performance metrics in this study were successfully achieved, with scores of 83.20 percent, 87.20 percent, and 79%, respectively.

To create a solid framework for diabetes prediction, Hasan *et al.*[12] employed the following Machine Learning (ML) classifiers, such as K-fold cross-validation, feature selection, data standardization, and outlier rejection. There is evidence to back up the idea that the weighted assembly of multiple machine learning models, where the weights are set by the corresponding Area Under Curve (AUC) of the ML model, can improve diabetes prediction. According to the Pima Indian Diabetes Dataset, the recommended classifier's performance metrics for sensitivity, specificity, false omission rate, diagnostic odds ratio, and AUC were 0.789, 0.934, 0.092, 66.234, and 0.950, respectively. Furthermore, it exceeded recent findings in AUC by 2.00%.

An efficient prediction algorithm for Diabetes Mellitus categorization on Imbalanced Data with Missing Values (DMP MI) was put forth by Wang *et al.* [13]. First, the missing values are corrected using the Naive Bayes (NB) approach for data normalization. An adaptive synthetic sampling technique (ADASYN), which lessens the effects of class imbalance, is then used to improve the prediction's performance. Predictions are made using a Random Forest (RF) classifier and then evaluated using a range of assessment markers. The effectiveness and superiority of the suggested DMP MI have been shown through experiments on the diabetes dataset for PIMA Indians from the University of California, Irvine (UCI) Repository.

The disease prediction model (DPM), which was put forth by Fitriyani*et al.*[14], consists of an ensemble approach to disease prediction, a synthetic minority oversampling method known as Tomek link (SMOTE Tomek), and an outlier identification method based on isolation forests (iForest) to weed out anomalous data. The result showed that the suggested DPM had the highest accuracy when compared to other models and past studies. The mobile application receives the prediction result when unexpected early-stage health situations arise, allowing prompt and appropriate action to be taken to reduce and prevent certain risks.

A process mining/deep learning architecture was proposed by Theis*et al.*[15] to improve existing severity score techniques by incorporating the medical histories of diabetic patients. The process of mining begins with the conversion of patient files from earlier hospital stays into event logs. Finding a process model that describes the patients' earlier hospital contacts will be done in the next step using the event logs. The in-hospital death of diabetic ICU patients is predicted using an application of decay replay mining that combines demographic and medical data with validated severity scores. This strategy is intended for hospitals with robust longitudinal patient records and may not be appropriate for those with a limited longitudinal patient history. The MIMIC-III database can be challenging to analyse because patients' treatments and diagnoses are requested for billing purposes without the matching occurrence timestamp.

Lekha and Suchetha presented a one-dimensional (1-D) modified convolution neural network (CNN) strategy that combines feature extraction and classification techniques. This paper's approach is shown to significantly lessen the drawbacks of utilizing these strategies solely, enhancing the performance of the classifiers. In this work, it is recommended that a modified 1-D CNN be used to handle real-time breath data collected from a variety of gas sensors. The experimentation and evaluation of the system's performance are done. The suggested technique has a shortcoming in that minimal interference in the response acquired from the MOS sensors owing to the influence of moisture in breath has not been explored. Furthermore, they only looked at a small number of patient data samples [16].

To predict the early onset of diabetes patients, Le *et al*. [17] suggested a novel wrapper-based feature selection strategy by optimizing the Multilayer Perceptron (MLP). Grey Wolf Optimization (GWO) and Adaptive Particle Swarm Optimization (APSO)are used in this technique. They also compared the outcomes of their methodology to some well-known machine learning methods. The computational findings of the suggested technique showed that it is also possible to attain greater prediction accuracy (96% for GWO-MLP and 97% for APGWO-MLP) with significantly fewer feature requirements.

Islam Ayon [18] suggested a method for training deep neural networks' characteristics using a five-fold and ten-fold cross-validation methodology to detect diabetes. The Pima Indian Diabetes (PID) data collection is accessible through the UCI machine learning repository database. With a prediction accuracy of 98.35%, an F1 score of 98%, and an MCC of 97% for five-fold cross-validation, the results on the PID dataset showed that deep learning may help to develop a useful system for the prediction of diabetes. Additionally, ten-fold cross-validation yields accuracy, sensitivity, and specificity values of 97.11%, 96.25%, and 98.80%. Results indicated that five-fold cross-validation enhances the performance of the proposed system.

For the identification and screening of diabetes, Nagaraj and Deepalakshmi [19] used an upgraded support vector machine and deep learning model. The suggested method makes use of a deep neural network that gets information from an improved support vector machine, hence enhancing the effectiveness of both systems as a whole. The dataset under consideration contains data on 768 individuals with eight critical criteria and a goal column that displays the outcomes as "Positive" or "Negative." According to the outcomes of the demonstration, a Python experiment showed that the deep learning model is superior at predicting diabetes.

A hybrid approach called the Genetic Algorithm-Extreme Learning Machine (GA-ELM) method was developed by Alharbi and Alghahtani using the dataset's first eight features. With a classification accuracy of 97.5% and six helpful factors, this technique has yielded an improved diagnosis of type 2 diabetes patients. Additionally, comparisons between the GA-ELM approach and other accessible methods were made, and the outcomes are encouraging [20].

Sneha and Gangil [21] centred on pointing out the shortcomings in the application of predictive analysis for the early detection of diabetes mellitus. When applied to diabetic data, the decision tree algorithm and Random Forest both had the highest specificity, with 98.20% and 98.00%, respectively. The best accuracy, according to the naïve Bayesian results, is 82.30. The best characteristics from the dataset are generalized in the study to increase classification precision.

3. Methodology

Untreated diabetes raises the risk of numerous other conditions, such as heart attack, heart failure, brain stroke, and many others, that, if left untreated, can be fatal. Therefore, it is crucial to identify diabetes early so that appropriate treatment may be performed and the condition can be stopped in its tracks to prevent future consequences. Figure 1 depicts the proposed system's overall model.

The patient data is first collected by IoT sensors and sent to a mobile application, where it is transferred to the cloud layer. Then, it is processed and categorized using a deep learning model. Lastly, a mobile application will be used to send all information to the medical team for treatment as represented in Figure 1.

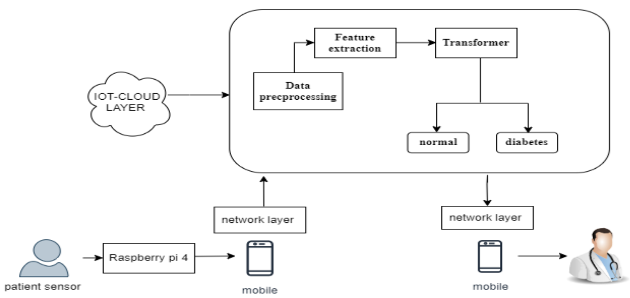

Figure 1: Overview of the proposed Transformer based diabetes prediction model

The glucose sensor on the IoT device senses the required data and transfers data to the mobile application using the raspberry pi 4 module. Then, the network layer has WAN, which enables real-time data transport from intelligent devices to the cloud. Patient data is stored in the cloud and sent to the deep learning module.

The cloud layer consists of a deep learning module and cloud storage. The patient's data are analyzed by the DL module, which evaluates the patient's health. Diabetes will be recognized by the transformer and saved on the hospital computer. Then, specialist monitor patients and examine the clinical information and results obtained via the mobile application.

3.1 Pre-processing

The process of diagnosing begins with this step. It has three steps: separation, redundancy elimination, and attribute replacement for those that are absent. After examining the patient's age group, BMI, insulin, and blood pressure levels, the missing value of a particular characteristic is substituted. A value is substituted in the same position if the majority of an attribute value for a patient match. By removing duplicate (irrelevant) characteristics, redundancy reduction shrinks the amount of data.

3.2 Feature selection

The method for reducing the number of features in a dataset while maintaining crucial pertinent information is feature selection [2]. Finding pertinent data and excluding irrelevant data are the objectives of feature selection. They are used to increase training accuracy and efficiency of the model.

Chi-square is used to pinpoint the feature. The independence between the feature and its corresponding class label is assessed using the chi-square X_C^2 test.

Chi-square analysis examines how far the feature O and predicted label E diverge from one another. The degree of freedom c is a measure of the power to reject the null hypothesis. The hypothesis of independence should be rejected if the chi-square value is high since the class and the incidence of the feature are connected, and the feature should be used in classification research. The appropriate definition is shown in Equation (1)

$$X_C^2 = \sum \frac{(O_{i-E_i})^2}{E_i} \quad (1)$$

After the feature selection now the transformer module will predict diabetes and classify the normal and diabetic data.

3.3 Transformer encoder architecture

The data are given as input to the transformer module which is made up of a position-embedded encoder block. The data are transformed into vector forms after the position embedding. The data is subsequently processed through the encoder stack. In general, the transformer architecture is constructed by combining the layers of multi-self-attention heads, a fully-connected layer, a pooling layer, a dropout layer, and a dense layer. A pictorial representation of this Transformer architecture is shown in Figure 2.

In the general architecture of the transformer encoder, layer normalization and dropout layers are applied to the embedding, into which positional information is added before it enters the Transformer. To use this information to identify the sequence's order, the transformer must first have some knowledge of the tokens' relative or absolute positions in the sequence. Therefore, "positional encodings" at the base of the encoder should be included in the input embeddings.

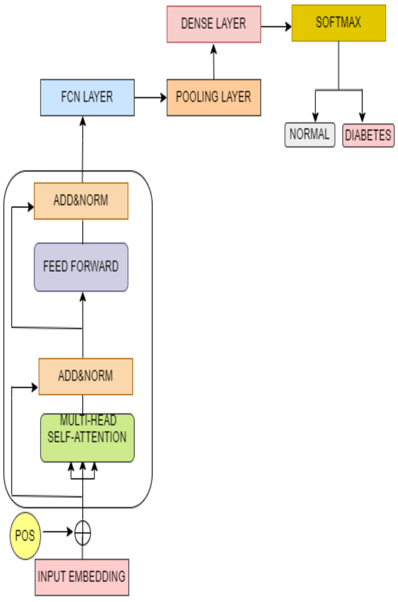

Figure 2: Transformer encoder

Here, a sine function is used to encode the even places, while a cosine function is used to encode the odd positions as shown in Equations (2) and (3) [1].

$$PE(pos, 2i) = sin(pos/1000^{2i/d_{model}}) \quad (2)$$

$$PE(pos, 2i+1) = cos(pos/1000^{2i/d_{model}}) \quad (3)$$

where pos is the position and i is the dimension.

The input attention layer of the Transformer uses a collection of queries (Q), keys (K), and values (v) as input to execute multi-head self-attention layers. The model uses multiple heads to simultaneously attend to data from a variety of representation subspaces placed at various locations as mentioned in Figure 3.

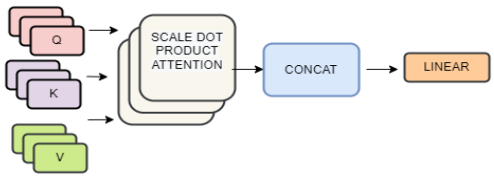

Figure 3: The multi-headed attention

Equation (4) is the multi-head attention's final result using a concatenated computing method.

$$Multihead(Q,K,V) = Concat(head_1 \ldots., head_a)W^0 \quad (4)$$

where h is the total number of heads.

The calculation method in multi-head is similar to single-head attention., as given in Equation (5). Each head must consist of:

$$Head_i = Attention\left(QW_i^Q KW_i^K VW_i^V\right) \quad (5)$$

where the projections are matrices of parameters $W_i^Q \in R^{dmodel \times d_k}, W_i^k \in R^{dmodel \times d_k}, W_i^v \in R^{dmodel \times d_k}, W_i^O \in R^{dmodel \times hd_k}$.

Following receipt of the attention score matrices from the Transformer, which includes the scores of each data set with unique attention patterns to combine the various attention scores of the words, the fully connected layer receives the features. Following the pooling layer, dropout layer, and final fully-connected layer, the class prediction of diabetes is discovered.

A final linear layer is utilized to convert the output, and the standard Softmax function is employed to calculate output probabilities, as mentioned in equation (6).

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{dk}}\right)V \quad (6)$$

Where d keys of dimension d_k. The Softmax function is used to calculate the weights on the values from the dot products of the query with all of the keys, and each value is divided by $\sqrt{d_k}$.After the prediction of diabetes, data are stored in the hospital server. Then the classified data are retrieved by the specialists through the mobile application and the medication is provided.

3.4 Dataset

The Pima Indian diabetes (PID) dataset is utilized in the suggested technique to predict and classify diabetes [2]. The dataset contains information on the likelihood of developing diabetes among 768 female patients older than 21 years, of which 268 samples tested positive for the disease and 500 tested negative. It has one output variable and eight characteristics, or input variables. Number of Pregnancies, Glucose, Blood Pressure (BP) (diastolic in mm Hg), Body Mass Index (BMI), Skin Thickness (mm), Insulin (muU/mL), Diabetes Pedigree Function, and Age are the variables used for analysis. Diabetes outcomes are categorized as 0 or 1.

3.5 Hyperparameter optimization

To train a model with noticeably greater performance, grid search optimization is employed. The most important hyperparameters while training a Transformer model are the learning rate and the number of training epochs. The hyperparameter information for the various batch sizes and grid search epochs is shown in Table 1.

Table 1: Hyperparameter optimization using grid search optimization with different batch sizes and epochs

Hyperparameters	Values
No. of. Layers	{1, 2,` 4, 8}
Number of epochs	25, 50, 75, 100
Multi-head attention sub-layer (h)	{2, 4, 8, 12, 16}
Key and value dimensions (dk)= (dv)	{32, 64, 128}
Batch size	{32, 64, 128, 256}
Learning rate	0.1
Drop out	0 to 1
Activation	ReLU, SoftMax
Optimizer	Adam

4. Result and discussion

The performance measure and findings obtained for the categorization and prediction of diabetes were emphasized in the following sections. There was also a comparison with earlier investigations. The success of the tactics being taught will be evaluated using the accuracy, recall, precision, and F1 score. After the transformer model was trained using 80% of the dataset, the remaining 20% was used for testing. For the proposed study, a binary classification with four possible outcomes—true positive, false positive, true negative, and false negative is used and the prognosis for diabetes is either normal or diabetes.

4.1. Performance metrics

❖ **Accuracy**

The primary indicator of a model's performance and efficacy is accuracy. The accuracy is calculated using (7).

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (7)$$

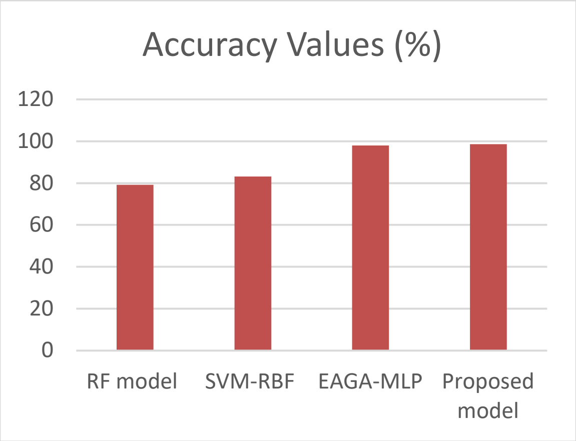

Figure 4: Comparison of Accuracy Value with other Techniques

According to Figure 4, the accuracy values of the suggested approach are greater than those of the previous methods (98.54%), the prediction of diabetes has likely been expanded and the true negative rate is likely to be high. Consequently, the proposed model reduces incorrect predictions.

❖ **Sensitivity**

Sensitivity is a statistic that is used to determine the percentage of correctly detected cases relating to real positives, as seen in (8).

$$sensitivity = \frac{TP}{TP + FN} \qquad (8)$$

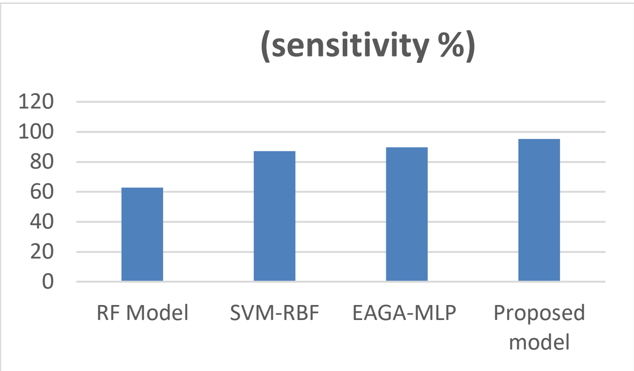

Figure 5: Comparison of Sensitivity Value with other techniques

Figure 5 demonstrates that the suggested approach's sensitivity values are higher than those of the previous method. It suggested that the prediction of diabetes has been improved, and the accuracy of the true positive rate is high (95.36%).

❖ **Specificity**

A statistic called specificity is employed to determine the ratio of correctly classified occurrences to truly positive instances, as indicated in Equation (9).

$$Specificity = \frac{TN}{TN + FP} \qquad (9)$$

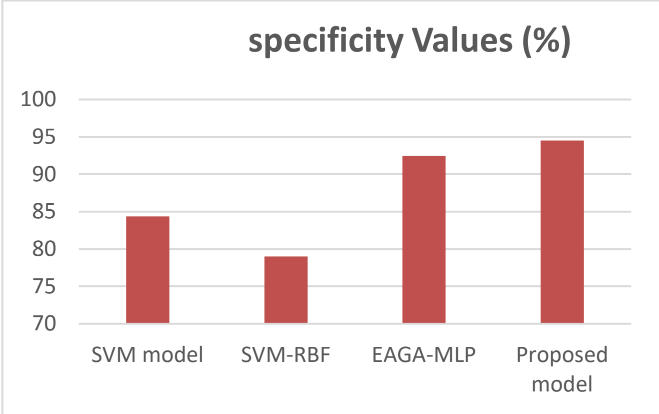

Figure 6: Comparison of Specificity Value with other techniques

Figure 6 demonstrates that the suggested method has greater specificity values than the earlier methods. With a true positive rate of 94.52%, it suggests that the prediction of diabetes has grown.

❖ **F1 Score**

Recall and precision are combined into a single score using F1-Measure. This calculation considers both false positives (FP) and false negatives (FN). It is depicted by the following formula (10).

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (10)$$

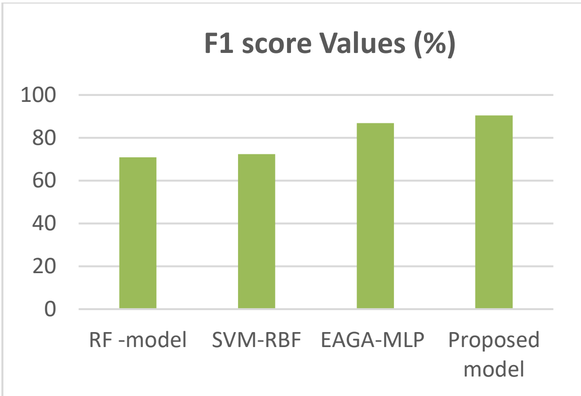

Figure 7: Performance analysis of proposed and existing techniques

As per Figure 7, the comparison analysis results, the suggested model's F1-score values of 92.58% are quite high when compared to earlier proposed strategies.

4.2. Receiver Operator Characteristic (ROC) curve

The Receiver Operator Characteristic (ROC) curve seems crucial for categorizing and identifying issues. This ROC is a probability curve that helps separate the signal from the noise by comparing the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold levels.

TPR, also referred to as sensitivity, describes the level of precision used to evaluate the negative class. How much of the negative class the model erroneously overestimates is shown by the FPR or specificity. The ROC curve's definition of AUC is an evaluation of a model's ability to distinguish between groups.

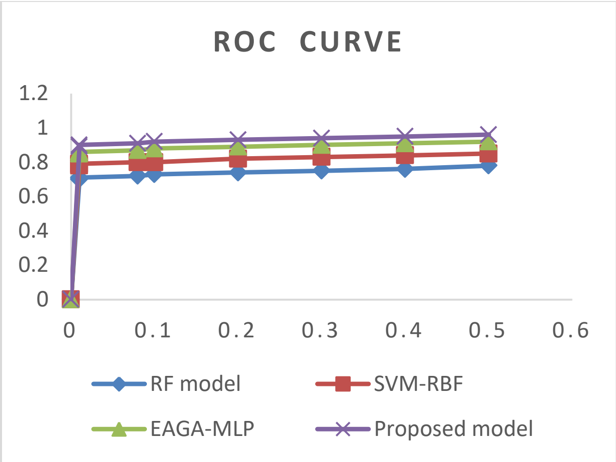

Figure 8: ROC CURVE

In Figure 8, the ROC curve which is located nearer to the top left corner than the existing work, demonstrates that the proposed work correctly identifies diabetes.

4.3. Confusion matrix

Both TP and TN demonstrate that a patient was appropriately recognized as a diabetic patient even though they did not have diabetes. Although the patient is supposed to be healthy, FN reveals that they have diabetes. Additionally, FP reveals that the patient is healthy, despite the diagnosis of diabetes.

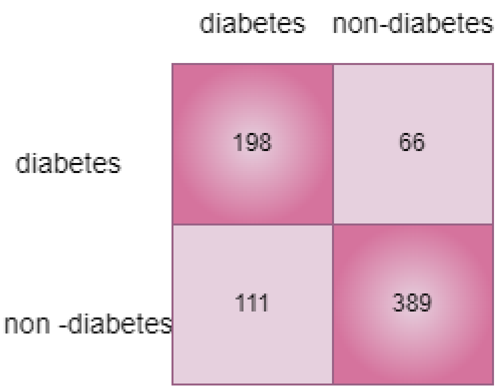

Figure 9: Confusion matrix

The confusion matrix for Figure 9 reveals that the normal data is 97.5% and the diabetic data is 98.6%. The accuracy is high when compared with the previous method so the computational time is reduced. The proposed system will reduce the misclassification of diabetes disease prediction.

5. Conclusion

Diabetes can affect people of any age, gender, or race. Diabetes kills its victims subtly. In severe, ongoing, life-threatening circumstances, diabetes may not even be discovered for many years. Using the PIMA Indian dataset, we attempted to build a learning model with IoT and transformer. The results of the transformer model showed how accurately objects are identified and categorized. Overall performance and accuracy scores of 98.54%, sensitivity levels of 95.36%, specificity levels of 94.52%, and F1 score values of 92.58% are improved by the suggested technique.

REFERENCES

[1] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, ‘‘Attention is all you need,’’ in Proc. Adv. Neural Inf. Process. Syst., 2017, pp. 5998–6008.

[2] X. Jiang *et al.*, “Towards an artificial intelligence framework for data-driven prediction of Coronavirus clinical severity,” *Comput. mater. contin.*, vol. 62, no. 3, pp. 537–551, 2020.

[3] *Pima Indians diabetes database*. (n.d.). Kaggle: Your Machine Learning and Data ScienceCommunity. https://www.kaggle.com/datasets /uciml/pima-indians-diabetes-database.

[4] Ramesh, J., Aburukba, R., &Sagahyroon, A. (2021). A remote healthcare monitoring framework for diabetes prediction using machine learning. *Healthcare Technology Letters*. https://doi.org/10.1049/htl2.12010

[5] Yahyaoui, Amani & Rasheed, Jawad & Jamil, Akhtar &Yesiltepe, Mirsat. (2019). A Decision Support System for Diabetes Prediction Using Machine Learning and Deep Learning Techniques. 10.1109/UBMYK48245.2019.8965556.

[6] Mishra S, Tripathy HK, Mallick PK, Bhoi AK, Barsocchi P. EAGA-MLP-An Enhanced and Adaptive Hybrid Classification Model for Diabetes Diagnosis. Sensors (Basel). 2020 Jul 20;20(14):4036. doi: 10.3390/s20144036. PMID: 32698547; PMCID: PMC7411768.

[7] Bhavya M R, Sanjay H C, Suraj S K, Savant AakashShivshankar Rao, Sanjay (2020) Diabetes Prediction using Machine Learning, International Journal of Engineering Research & Technology (IJERT) Vol. 9, Issue 7, July 2020

[8] U. Ahmed et al., "Prediction of Diabetes Empowered with Fused Machine Learning," in IEEE Access, vol. 10, pp. 8529-8538, 2022, doi: 10.1109/ACCESS.2022.3142097.

[9] Madan, P., Singh, V., Chaudhari, V., Albagory, Y., Dumka, A., Singh, R., AlGhamdi, A. S. (2022). An optimization-based diabetes prediction model using CNN and Bi-directional LSTM in real-time environment. Applied Sciences (Basel, Switzerland), 12(8), 3989. doi:10.3390/app12083989.

[10] MitushiSoni, Dr.Sunita Varma, 2020, Diabetes Prediction using Machine Learning Techniques, International Journal of Engineering Research & Technology (IJERT) Volume 09, Issue 09 (September 2020).

[11] Kadhm, Mustafa &Ghindawi, Ikhlas& N. Mhawi, Doaa. (2018). An Accurate Diabetes Prediction System Based on K-means Clustering and Proposed Classification Approach. International Journal of Applied Engineering Research. 13. 4038-4041.

[12] M. K. Hasan, M. A. Alam, D. Das, E. Hossain and M. Hasan, "Diabetes Prediction Using Ensembling of Different Machine Learning Classifiers," in IEEE Access, vol. 8, pp. 76516-76531, 2020, doi: 10.1109/ACCESS.2020.2989857.

[13] Q. Wang, W. Cao, J. Guo, J. Ren, Y. Cheng and D. N. Davis, "DMP_MI: An Effective Diabetes Mellitus Classification Algorithm on Imbalanced Data with Missing Values," in IEEE Access, vol. 7, pp. 102232-102238, 2019, doi: 10.1109/ACCESS.2019.2929866.

[14] N. L. Fitriyani, M. Syafrudin, G. Alfian and J. Rhee, "Development of Disease Prediction Model Based on Ensemble Learning Approach for Diabetes and Hypertension," in IEEE Access, vol. 7, pp. 144777-144789, 2019, doi: 10.1109/ACCESS.2019.2945129.

[15] J. Theis, W. L. Galanter, A. D. Boyd and H. Darabi, "Improving the In-Hospital Mortality Prediction of Diabetes ICU Patients Using a Process Mining/Deep Learning Architecture," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 1, pp. 388-399, Jan. 2022, doi: 10.1109/JBHI.2021.3092969.

[16] Lekha, S., and Suchetha, M., "Real-Time Non-Invasive Detection and Classification of Diabetes Using Modified Convolution Neural Network," in IEEE Journal of Biomedical and Health Informatics, vol. 22, no. 5, pp. 1630-1636, Sept. 2018, doi: 10.1109/JBHI.2017.2757510.

[17] Le, T. M., Vo, T. M., Pham, T. N., & Dao, S. V. T., "A Novel Wrapper–Based Feature Selection for Early Diabetes Prediction Enhanced with a Metaheuristic," in IEEE Access, vol. 9, pp. 7869-7884, 2021, doi: 10.1109/ACCESS.2020.3047942.

[18] Safial Islam Ayon, Md. Milon Islam, "Diabetes Prediction: A Deep Learning Approach", International Journal of Information Engineering and Electronic Business (IJIEEB), Vol.11, No.2, pp. 21-27, 2019. DOI: 10.5815/ijieeb.2019.02.03

[19] Saravanan, T., Nagadeepa, N., Mukunthan, B. (2022). The Effective Learning Approach to ICT-TPACK and Prediction of the Academic Performance of Students Based on Machine Learning Techniques. In: Sharma, H., Shrivastava, V., Kumari Bharti, K., Wang, L. (eds) Communication and Intelligent Systems. Lecture Notes in Networks and Systems, vol 461. Springer, Singapore. https://doi.org/10.1007/978-981-19-2130-8_7

[20] P. Nagaraj and P. Deepalakshmi, "Diabetes prediction using enhanced SVM and Deep Neural Network learning techniques: An algorithmic approach for early screening of diabetes," Int. J. Healthc. Inf. Syst. Inform., vol. 16, no. 4, pp. 1–20, 2021.

[21] A. Alharbi, M. Alghahtani, Using genetic algorithm and ELM neural networks for feature extraction and classification of type 2-diabetes melIitus. Appl. Artif. Intell. 33(1-4), 311–328 (2019).

[22] Sneha, N., &Gangil, T. (2019). Analysis of diabetes mellitus for early prediction using optimal features selection. *Journal of Big Data*, *6*(1). doi:10.1186/s40537-019-0175-6

[23] J. Ramesh, R. Aburukba, and A. Sagahyroon, A RemoteHealthcare Monitoring Framework for Diabetes Prediction Using Machine Learning, Healthcare Technology Letters, UK, April 2021.