

DIABETES MELLITUS PREDICTION FRAMEWORK USING ARTIFICIAL NEURAL NETWORK MODELS

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ABSTRACT

With increased occurrence of diabetes mellitus, novel mechanisms for its early and precise detection, and strategies for its control are required. The disease poses increased risk of the onset of cardio-vascular and kidney ailments, among others, and when uncontrolled, may prove lethal. This study designs an Artificial Neural Networks (ANN) model for diabetes detection, varying learning rate, and examining its behavior on prediction accuracy. A novel diabetes dataset trained the ANN models, which were compared using performance metrics. Highest accuracy of 88.0% was observed in a three hidden layer ANN model. Hybrid and ensemble algorithms, on the novel dataset, would be developed in the future and their performance compared. A complete plan for diabetes management requires the integration of deep learning-based predictor models, with clinical practice. This would aid in a cost-effective mechanism for this global disease.



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1. INTRODUCTION

Diabetes mellitus is a chronic and lifelong metabolic disorder that is identified by consistent high blood glucose levels. The condition results from inadequate insulin production by the pancreas, and or the reduced insulin action. The non-regulation of glucose levels leads to progressive metabolic imbalance. The mismanagement of the disease leads to long-term damage to vital organs. The World Health Organization (WHO) has also reported that uncontrolled diabetes increases the risk of cardiovascular disease, kidney failure, diabetic retinopathy (loss of vision), and

neuropathy (nerve damage). Severe diabetes cases may lead to disability and premature mortality (World Health Organization, 2024). Recent global studies reported by The Lancet, emphasize the extent of this disease, with data proving the sharp rise in worldwide cases (Zhou et al., 2024).

With the growing incidence of diabetes, it is now a global health concern. Projections from the International Diabetes Federation (IDF) Diabetes Atlas (11th Edition) highlight the degree of increase of diabetes cases. This work partitioned the world into seven regions. The report estimates that by 2050, there would be an astonishing

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45% global increase in diabetes cases in adults (of age 20 to 79), as compared to 2024, raising the number to a projected 853 million. The projected increase is disproportionate across regions, with a predicted increase of 145%, 92% and 10% in African (AFR) region, Middle East and North Africa (MENA) region, and Europe (EUR) respectively. The projected increase in diabetes cases (from 2024 to 2050), for the seven regions is given in Table 1 (IDF Diabetes Atlas 11th Edition - 2025, 2025). WHO has reported that globally 14% of adults in 2022 were diabetic, which was a 7% increase since 1990. A report in 2021 stated diabetes as the principal cause of 1.6 million deaths, 11% cardiovascular deaths and 530,000 kidney disease deaths (World Health Organization, 2024). A landmark Lancet study of nearly 200 countries and territories, examined global diabetes trends (its prevalence and treatment) between 1990 and 2022. The study revealed that 828 million adults were living with diabetes in 2022, an astonishing increase of 630 million diabetes cases since 1990. The results revealed that the sharpest rises in diabetes cases occurred in low and middle-income countries, where there was rapid urbanization and lifestyle changes, ageing population, but the population had limited access to preventive diabetes care (Zhou et al., 2024). All these studies further establish the urgent need for region-specific policies for prevention and care of diabetes

Table 1. Region wise increase in diabetes cases (from 2024 to 2050).

Region	Increase in Cases (%)
Africa	142
Middle East & North Africa	92
South-East Asia	73
South & Central America	45
Western Pacific	18
North America & Caribbean	21
Europe	10

Diabetes mellitus is commonly classified into type 1, type 2, and gestational diabetes. Type 1 diabetes is an autoimmune condition that typically begins in childhood or adolescence, where there is little or no insulin production in the body. The most common, type 2 diabetes, develops due to insulin resistance and inadequate insulin secretion, and typically occurs in adults. Research has linked the onset of diabetes to lifestyle factors such as unhealthy diet, physical inactivity, and obesity, among others. Though generally non-reversible, type 2 diabetes can be successfully managed, giving patients a comfortable life. This can be achieved through dietary changes, regular exercise, weight management, and medication. The third type, gestational diabetes, occurs during pregnancy, when hormonal changes impair insulin action. This condition is generally resolved after childbirth, nonetheless it increases future diabetes risk. Uncontrolled diabetes

leads to serious complications, including bone disorders, neuropathy, retinopathy, diabetic foot, and reduced immunity. Due to its high prevalence, type 2 diabetes requires early detection, close monitoring, and a long-term management strategy.

To improve the early and accurate detection of diseases, a variety of computational and data-driven approaches have been investigated by researchers, with rapid advancements occurring in the last decade. The availability of high-speed systems has aided in recent research having increasing focus on implementing of machine learning (ML) models, deep learning (DL) models, ensemble models, and hybrid models in disease detection, treatment and management. The growing availability of large and complex healthcare datasets, have facilitated experimenting with these models. For diabetes prediction, algorithms such as Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), support vector machines (SVM), decision trees, and ensemble learning techniques have been extensively used to classify individuals as diabetic or non-diabetic. These models are effective at capturing the non-linear relationships and among key clinical and demographic variables (glucose, insulin levels, body mass index (BMI), age, and other metabolic indicators), which are generally difficult to interpret using traditional statistical methods. Due to this capability of identifying meaningful patterns and associations within medical data, machine learning based approaches have proven as the correct choice for developing models for accurate and early risk identification and personalized patient care (Baranwal & Tharakaram, 2025). These optimized models can support clinicians in timely decisions, enabling preventive interventions, and improved long-term diabetes management.

The wide use of artificial intelligence (AI) and ML for disease prediction has shown substantial improvement in diagnostic accuracy and resulted in patient care systems that are customized to the patient's needs. Deep learning algorithms like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have shown to be highly effective when dealing with complex datasets, like medical images. By creating mobile health applications that monitor data received from wearable devices, real-time patient monitoring has become a reality. This provides timely intervention, giving a new dimension to diabetes management strategies, thereby bridging the gap between state-of-the-art research and modern healthcare solutions (Alam et al., 2024). SHAP (SHapley Additive exPlanations) aids in uncovering a model's decision-making process of prediction (Nimmagadda et al., 2024). With the evolving health-care needs, integrating real-time data collection with these models enhances the model's adaptability, making them robust. Data scientists, healthcare professionals and policy makers need to join to formulate a comprehensive mechanism for diabetes prevention and management.

Several predictive models have been successfully integrated into routine medical practice, assisting clinicians in early detection of the disease. These models also aid in quick identification of individuals that are at high-risk in contracting a disease, enabling prompt intervention before complications arise. Since type 2 diabetes is a lifelong condition, its early detection and care, reduces the risk of related complications. Patients can adhere to suitable lifestyle changes, with treatment that control symptoms and reduces the progression and side effects of the disease. With early and accurate diabetes diagnosis, therapeutic strategies can be customized for each patient, ensuring effective treatment. This not only enhances clinical outcomes but also attributes to an improved quality of life, increasing the life expectancy for individuals with this life-long disease

The remainder of this paper is structured as follows. Section 2 reviews related work on global diabetes trends and machine learning and deep learning approaches for disease prediction. Section 3 details the dataset, preprocessing, methodology, and evaluation metrics. Section 4 presents and analyzes the experimental results, while Section 5 concludes the study and outlines directions for future research.

2. RELATED WORK

With the growing global incidence of diabetes mellitus, there is a constant need for accurate and timely diabetes prediction. Studies have been conducted on parameters that aid in diagnosis and monitoring of diabetes mellitus. Models based on ML and DL techniques have been designed for accurately predicting diabetes on diverse diabetes datasets. With significant research scope in this area, researchers have been devising various methodologies for timely and accurate disease prediction.

A study categorized heart disease in Cleveland UCI repository using machine learning algorithms. The Random Forest (RF) gave best accuracy of 89% (Mishra et al., 2024). Yet another research on this disease compared six ML models: KNN, Logistic Regression (LR), Decision Tree (DT), SVM, RF, and Gradient Boosting (GB). The Adaptive Synthetic Sampling Approach (ADASYN) class balancing technique presented 81% accuracy in RF classifier (Sadar et al., 2024).

The ANN's inherent capability of feature extraction has been one of the reasons for its extensive use by researchers. This technique has been widely used by researchers as it results quicker model training time, which is significant time saved when applied to larger datasets. Research on the Pima Indians Diabetes (PID) dataset used three layers (input, output and one hidden layer), 0.0005 learning rate and Adaptive Moment Estimation (Adam) optimizer. The classifier

demonstrated an accuracy of 80.79% (Pyne & Chakraborty, 2023). Another study on this dataset developed multiple ANN models which varied in number of hidden layers and the number of neurons in the hidden layers, using Root Mean Square Propagation (RMSprop) and Adam optimizers for training. Models were trained with diverse epochs. The maximum accuracy of 84.42% was displayed by the ANN model that used Adam optimizer and three hidden layers (Adlakha et al., 2025).

Further studies on the PID dataset compared the performance accuracy of SVM, RF and multi-layer perceptron (MLP) algorithms. The ANN model with 12 hidden layer neurons, 500 epochs demonstrated an accuracy of over 84% (Sahu & Mantri, 2023). A study designed a model for diabetes prediction for the Mansoura University Children's Hospital Diabetes (MUCHD) dataset and proposed a Deep Neural Network (DNN) based on MLP algorithm-based model. With 10 hidden layers, epochs, and fine tuning multiple hyperparameters on the DNN model, the ideal model was obtained. This model displayed 99.8% accuracy, and resulted in 0.39% increase in the overall system performance, when compared to other state-of-the-art algorithms (El-Bashbishy & El-Bakry, 2024).

Another study proposed a diabetes forecast model on Kaggle data. This model compared prediction accuracy of ML algorithms - SVM, LR, Naïve Bayes, RF; and ensemble techniques - Adaboost, CatBoost, XGBoost, LightGBM, bagging. The CatBoost model displayed the highest accuracy of 95.4%, and the XGBoost model displayed a slightly lower accuracy of 94.3% (Modak & Jha, 2024).

Studies focusing on the learning rate used for training ANN networks have shown noteworthy results. The learning rate has shown a significant influence on the convergence capability; the stability and generalization of the Adam optimizer used in ANN training. A recent study suggests that a learning rates of 0.05 could be too large, when used with specific batch sizes, resulting in lower prediction accuracy. Being closer to the sweet optimum, models trained with lower learning rates of 0.0005 or 0.005 frequently display higher prediction accuracy (Li et al., 2024).

The quantifiable indicators of various biological processes, biomarkers, may be regularly screened, for early disease detection. In a recent study, explainable artificial intelligence (XAI) technique was employed to identify the biomarkers related to clinical, pathological and demographic attributes which assist in early diabetes detection. Their proposed model was implemented on multiple datasets. This study concluded that people above forty years, and Body Mass Index (BMI) value greater than 26, need to be frequently checked for glucose or Hemoglobin A1c (HbA1c) (Ahuja & Indra, 2024).

Research on diabetes prediction has investigated the performance of models developed using various techniques on diverse datasets, and the effect of hyperparameter tuning on model performance, among others. Table 2 provides a summary of related work.

On studying previous related work, gaps and future scope of work were identified. Diverse standardized diabetes

datasets are required, to further test the robustness of models. The study of the effect of hyperparameter tuning on the performance of ANN model, especially when applied to new standardized datasets is required. The focus of this study is to design an optimized diabetes mellitus prediction framework that can be generalized across diverse datasets.

Table 2. Summary of related work.

S. No.	Reference	Dataset and Model Description	Performance
1.	(Pyne & Chakraborty, 2023)	Pima Indians Diabetes (PID) dataset ANN models (input, output & one hidden layer, 0.0005 learning rate, Adam optimizer)	80.79% accuracy
2.	(Sahu & Mantri, 2023)	PID dataset ANN models (hidden layers, learning rate)	84% accuracy (2 hidden layers, 0.01 learning rate)
3.	(Sadar et al., 2024)	Models: KNN, LR, DT, SVM, RF, and GB models ADASYN class balancing technique	Best accuracy of 81% by RF classifier
4.	(Adlakha et al., 2025)	PID dataset ANN model (hidden layers, Adam/ RMSprop optimizers, epochs)	84.42% accuracy (3 hidden layers, Adam optimizer, 500 epochs)
5.	(Sarkar & Pawar, 2023)	PID dataset ANN with parameter tuning	96.35% accuracy
6.	(El-Bashbishy & El-Bakry, 2024)	Mansoura University Children's Hospital Diabetes dataset Deep Neural Network based multi-layer perceptron algorithm (10 hidden layers)	99.8% accuracy
7.	(Al Reshan et al., 2024)	i) PID dataset ii) Frankfurt Hospital Germany dataset iii) Iraqi Diabetes Patient Dataset Ensemble learning based stacking models (stack-ANN, stack-CNN, stack-LSTM (Long Short-Term Memory))	stack-ANN respective accuracy on three dataset - 99.51%, 98.81%, 98.45%
8.	(Tripathy et al., 2024)	PID dataset Models based on deep neural networks	Best accuracy of 93% by LSTM model
9.	(Modak & Jha, 2024)	Kaggle dataset Standalone models - SVM, LR, Naive Bayes, RF Ensemble models - Adaboost, bagging, CatBoost, LightGBM, XGBoost	Best accuracy of 95.4% by CatBoost model
10.	(Sarkar & Das, 2025)	Dataset from cross-sectional & observational study conducted at Guwahati Medical College, Assam, India ML & ANN models	Models based on neural network model outperformed SVM & Bayes model
11.	(Li et al., 2024)	ANN model with Adam optimizer	Lower accuracy with higher learning rates (0.05) Higher accuracy with lower learning rates (0.005, 0.0005)

3. MATERIAL AND METHODS

3.1 Methodology

Using ANN, a diabetes mellitus prediction framework is developed in this study. Figure 1 shows the steps followed to develop this framework. Data is first retrieved from the novel diabetes dataset. Subsequently data pre-processing steps of data cleaning, data wrangling, feature extraction and scaling is done. The pre-processed data is used to develop the prediction framework, using ANN models. Model evaluation, and

analysis (through performance metrics) is done. This process is repeated, as the model is fine turned, changing its hyperparameters, until an ideal optimized model is obtained. The performance of the models is accessed through accuracy and other parameters (precision, recall, F1 Score, AUC) . The optimized model is deployed for future use by integrating it with a real-world clinical application. These applications are monitored and maintenance is ensured, so that the model's performance is consistent over time. This step is essential so that the application can be actively used for a decision-support system for diabetes management.

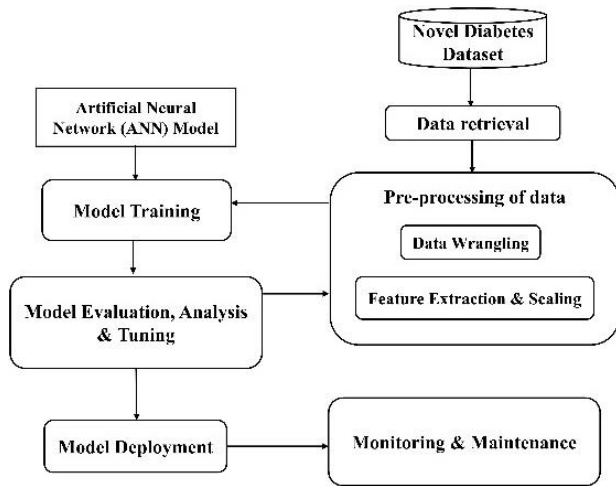


Figure 1. Methodology of the proposed model for prediction of diabetes

3.2 Dataset Description

This study uses the Novel Diabetes Dataset, using its female records. The dataset has five input features (Gender, Age, BMI, Glucose, BloodPressure) and one output feature (Diabetes). This dataset has 3820 records, where participants are of age 21 and above. There are 2446 (64.03 %) females records and 1374 (35.97 %) male records in this diabetes dataset (Adlakha, Mona, 2025). This is a sample dataset that is being used for implementing ANN models.

3.3 Data Pre-processing and Analysis

Dataset analysis reveals the number of missing values, null values, and outliers. ANN models automate the step of feature extraction, by learning from features (raw input). The association between dataset features is assessed through their correlation. Strongly correlation features are significant criteria in disease prediction.

The data distribution of individual features is interpreted through its skewness. Skewed data causes ML and DL models to generate biased predictions. To resolve this, a feature scaling technique (standardization or normalization) is applied to the model. These techniques rescale the data, ensuring that models are robust in their predictions.

The ‘StandardScaler’ technique standardizes the numeric feature values. Once applied, the dataset features have mean value of 0 and a standard deviation of 1. For a sample x , with s as the standard deviation of training samples, and u as its mean; the scaled value z is obtained as in Equation 1:

$$z = \frac{x-u}{s} \quad (1)$$

3.4 Deep Learning Algorithm

Once the data is cleaned and scaled, it is ready to be used for developing the ANN model classifier, using the training set. An open-source python-based ML framework was used to implement these models. The model then predicts the target feature ‘Diabetes’ using the test set.

As compared to test:train ratio of 75:25, better performance was observed when models were designed with ratio of 80:20. All models were developed in this study used the 80:20 ratio for test:train split. Adam optimizer demonstrates higher model performance (Adlakha et al., 2025). This optimizer was thus chosen for training all the ANN models that were designed in this study. Lower learning rates displayed higher accuracy of prediction (Li et al., 2024). This study designed ANN models with variations in the learning rate (0.005, 0.0005) and epochs (20, 50, 100).

Assuming N_1 , N_2 , N_3 are the number of neurons in three hidden layers of the ANN model, below is the pseudocode:

1. Load the dataset.
2. Do data preprocessing: data cleaning, feature analysis & standardize data.
3. Split the data for training & testing, in ratio of 80:20.
4. Model selection - ANN:
 - a. Create a neural network: For each layer, add a Dense layer, using ReLu activation function for hidden layers, and Sigmoid function for outer layer
 - b. Model fitting with learning rates (0.005, 0.0005)
 - c. Compile model with Adam optimizer.
5. Do model training & evaluate the model using performance metrics.
6. Graphically visualize accuracy and loss curves for training and validation.

3.5 Model Evaluation Using Performance Metrics

Subsequent to model training on a training set, model is tested on the test set. This assesses the model’s performance in predicting the output ‘Diabetes’ (1:diabetic patient or 0:non-diabetic). The confusion matrix gives the counts of: true positive (TP), false positive (FP), true negative (TN), and false negative (FN). These are used to determine the performance metrics.

The model’s accuracy measures the correct predictions, i.e. the fraction of instances that are correctly classified, as in Equation 2:

$$accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

The model's precision is the fraction of true positive instances, out of all instances that are predicted as positive, as in Equation 3:

$$precision = \frac{TP}{(TP+FP)} \quad (3)$$

True Positive Rate (TPR) or recall, is the fraction of the true positive instances out of all instances that are actually positive, as given in Equation 4:

$$recall = \frac{TP}{(TP+FN)} \quad (4)$$

F1 score measures accuracy of the test. It is the harmonic mean of precision and recall, as given in Equation 5:

$$F1\ score = 2 * \frac{(precision * recall)}{(precision + recall)} \quad (5)$$

The False Positive Rate (FPR), is the fraction of true negative instances out of all the actual negative instances, as given in Equation 6:

$$False\ Positive\ Rate\ (FPR) = \frac{FP}{(FP+TN)} \quad (6)$$

The True Positive Rate (TPR) and the False Positive Rate (FPR) can be graphically plotted on the y-axis and x-axis respectively. The resultant graph is called the receiver operating characteristic (ROC) curve. The Area Under the Curve (AUC) is a value that lies between 0 and 1. This is a quantitative measure of the ability of a model to differentiate between the positive and negative classes. For medical research, a minimum AUC score of 0.8 is sufficient for the model to be effective for medical prediction. During training and validation phases, the accuracy and loss curves monitor the behavior of the model during these phases. Curves that converge and then subsequently stabilize show that the model does not display overfitting, and is thus consistent in its performance. Such models display good generalization, are reliable and therefore are robust models for use in medical predictions.

4. STUDY RESULTS AND DISCUSSIONS

4.1. Data Analysis Results

Analysing the implementation of ANN models on the novel diabetes dataset, the generated descriptive statistics provides the key metrics, exhibiting no null values in the feature data. Among the 2446 female data of the dataset, analysis showed that 1978 (80.87%) cases were non-diabetic and 468 (19.13%) cases were diabetic, as depicted in Figure 2. There is an imbalance in non-diabetic and diabetic cases. Results showed that more diabetic cases are reported in individuals with higher BMI, as compared with those of lower BMI.

Correlation of the dataset features indicates weak or strong relationship between them. The resultant heatmap from the correlation studies of this dataset is given in the

Figure 3. The correlation lies between -0.09 and 0.54, indicating weak or moderate feature correlation. Low values of correlation between 'Age' and other features indicate weak correlation. Correlation values for features 'BMI' and 'Glucose'; 'BMI' and 'BloodPressure'; and 'BMI' and 'Diabetes', indicate moderate positive correlation between these features. The highest correlation is displayed between 'Glucose' and 'Diabetes', which indicate that individuals with higher glucose levels have a higher incidence of diabetes.

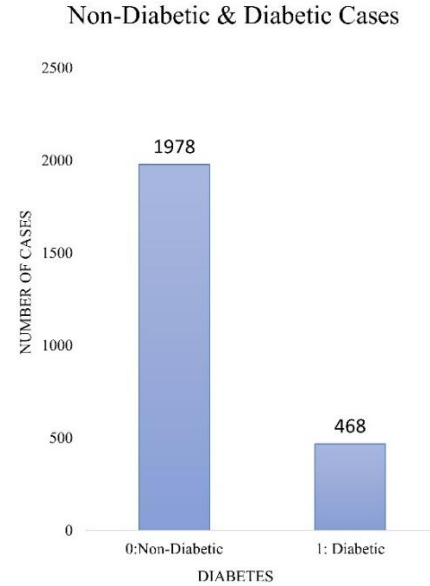


Figure 2. Non-Diabetic and diabetic cases

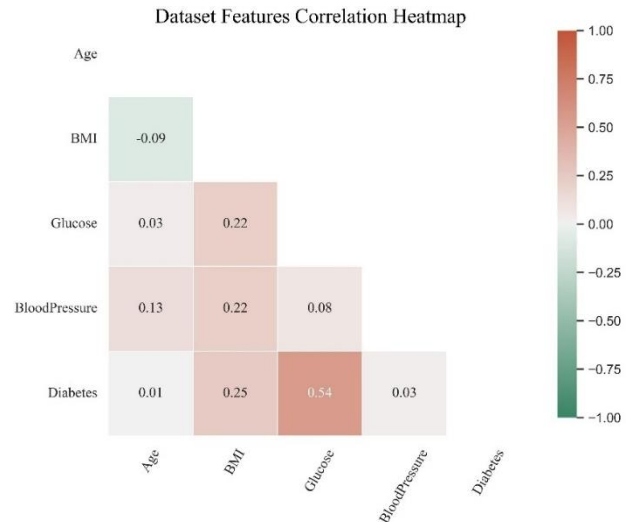


Figure 3. Dataset features correlation heatmap

Figure 4 shows the skewness of dataset features. The highest skewness value of 3.03 was observed in the feature 'Glucose'. 'Age', 'BloodPressure' and 'BMI' too displayed skewed distribution (skewness value of 0.14, 0.41, 0.84 respectively). Machine learning models give biased predictions when there are skewed distributions of features. Standardization, a feature scaling method, was thus applied to the dataset. This makes the predictions made by the model more stable, resulting in a robust model.

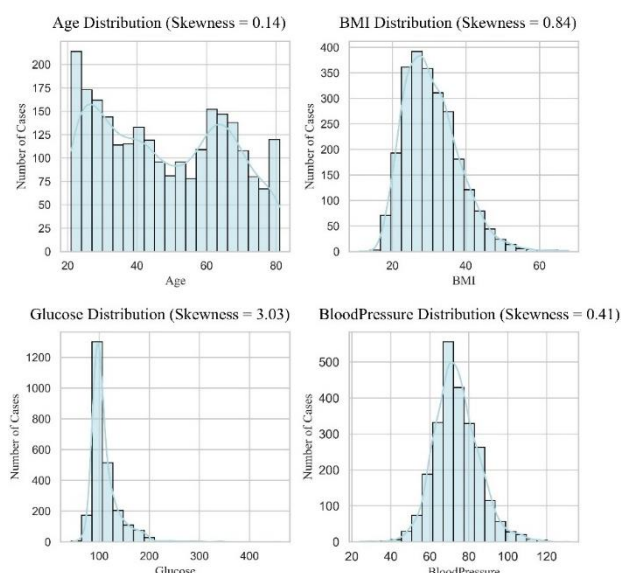


Figure 4. Parameter skewness in diabetes dataset

4.2. Results of Deep Learning Models

ANN models with varying number of hidden layers were developed on select (female) data from of the novel

diabetes dataset. Initial models varied in the hyperparameters learning rate (0.05, 0.005, 0.0005), with varying epochs (20, 50, 100, 500) and model training using Adam optimizer. Higher accuracy was observed in models with 0.005 and 0.0005 learning rates; and 20, 50, and 100 epochs. Using these learning rates and epochs, ANN models were designed with variation in number of hidden layers and its neurons, keeping 80:20 as the train:test ratio.

Model evaluation of these ANN models was done. On evaluating these metrics, it was observed that models varied in their accuracy and other performance parameters. The maximum accuracy of Diabetes (no diabetes, or diabetes) prediction was observed as 88.0%. This accuracy was achieved by the 3 hidden layer model which was trained with Adam optimizer, 20 epochs, 0.0005 learning rate and number of neurons in hidden layers (N1: 32, N2: 16, N3: 8). The other performance parameters of this model being precision: 0.722, recall: 0.606, F1 score: 0.659, FPR: 0.056, and AUC score: 0.887, as shown in Table 3. All the ANN models developed in this study demonstrated excellent AUC scores ranging from 0.883 to 0.891, proving the validity of the models.

Table 3. Results of Proposed Diabetes Mellitus Prediction Framework Using ANN Model.

Accuracy (%)	Precision	Recall	F1 Score	False Positive Rate (FPR)	AUC Score
88.0	0.722	0.606	0.659	0.056	0.887

Another important aspect for studying the performance of a model is to access the behavior of the model's accuracy and loss curves during training and validation. As a demonstration, two such curves, of an ANN model (3 hidden layers, 0.0005 learning rate, 50 epochs), are discussed. Figure 5 depicts the Accuracy (Training and Validation) Curve and Figure 6 depicts the Loss (Training and Validation) Curve. These graphs (in 600 dpi), give a graphical description of the behaviour during training and validation; accuracy vs epochs, and loss vs epochs.

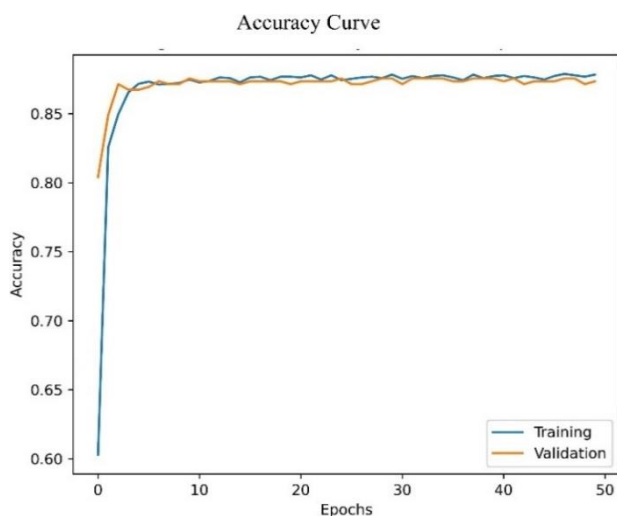


Figure 5. Accuracy Curve (during Training and Validation)

Figure 5 illustrates the training and validation accuracy of the ANN model. The figure shows that by the fourth epoch the training accuracy smoothly increases to 0.88 (88%), and subsequently there are only slight variations in accuracy till the fiftieth epoch. The accuracy during validation phase initially begins at 0.81 (81%), and by the third epoch the accuracy reaches 0.88, after which it displays slight fluctuations till fiftieth epoch.

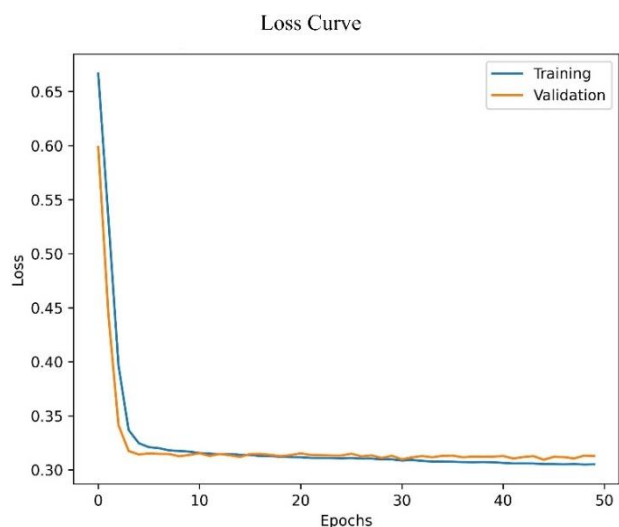


Figure 6. Loss Curve (during Training and Validation)

Figure 6 shows that, during the model's training and validation, both the loss curves show a significant decline, both in tandem till the tenth epoch. The loss value for both the curves remains as nearly the same low value between tenth and thirtieth epoch, with both curves nearly overlapping. Both curves run parallel to each other after thirtieth epoch, displaying a minimum loss.

Analyzing the accuracy and loss curves, we infer that the model exhibits a satisfactory fitting. There is close alignment in training curve and validation curve, for accuracy as well as loss. No overfitting is observed when the training is extended to fifty epochs. The accuracy neither increases significantly, and the loss does not decrease significantly in the latter epochs.

Further it may be inferred that, for some situations, early stopping can be implemented, to stop the model training process. This is possible because, after some epoch, there is insignificant variation in the accuracy and loss curves (during training as well as validation). The reduced training time further reduces the model's overall computation time, leading to faster diabetes prediction. Datasets are generally noisy, for medical datasets used for diabetes prediction. The overlapping of these curves (accuracy and loss curves for training and validation), prove that the designed ANN model is effective in establishing the relationship between the clinical features of the dataset. Without overfilling, this model is ideal for disease prediction, as it is stable.

5. CONCLUSION

This study developed Artificial Neural Network (ANN) models on the Novel Diabetes dataset, using its female records. The models are implemented with the Adam optimizer and multiple hidden layers, with models varying in number of hidden layers and learning rate.

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Performance of multiple models was compared based on the accuracy and other performance metrics (precision, recall, F1 score, FPR and AUC score). The ROC Curve demonstrated that very large or small epochs resulted in lower accuracy. As compared to 0.05 learning rate, 0.005 and 0.0005 learning rates demonstrated better performance. The highest accuracy of 88.0% was displayed by the three hidden layer model with 0.0005 learning rate and Adam optimizer.

Epochs during model training aid in monitoring the accuracy and loss (for training and validation). These allow the model to improve the values of its hyperparameters and generates an optimized model. In several models, the accuracy and loss stabilize after a specific epoch. Early stopping may be implemented to stop the training, and save execution time. Substantial execution time would be saved for larger datasets. The convergence of the accuracy and loss curves confirm that this proposed ANN model is perfect in establishing accurate relationships among clinical features of a dataset. This robust model thus provides the stability and generalization that is essential for a clinical decision support system employed in diabetes prediction.

The results exhibit the high performance of ANN models when applied to a standardized dataset. Future experiments would apply early stopping. Further, it would be interesting to study the performance of hybrid and ensemble models on this novel diabetes dataset. This research plays a vital role in providing a framework for accurate diabetes prediction, that may be integrated with clinical practice, contributing to the persistent worldwide effort for managing diabetes mellitus.

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