A Study On Type 2 Diabetes Prediction Using Deep Learning Techniques

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Abstract- *T2DM, or type 2 diabetes mellitus, has become a major global health concern due to its high prevalence and related medical expenses. With an emphasis on data-driven strategies that make use of patient health information, such as blood sugar levels, body mass index (BMI), and other lifestyle-related indicators, this study investigates many deep learning algorithms for type 2 diabetes prediction. we use a number of deep learning algorithms to evaluate and compare how well they predict diabetes: Artificial Neural Network (ANN), Feedforward Neural Network (FNN), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN). With a prediction accuracy of 95.27%, the GRU outperforms other strategies, according to the study, which highlights the benefits and drawbacks of each approach using metrics including accuracy, precision, recall, and F1 score. According to the results, deep learning models—in particular, GRU and CNN—have a great deal of potential for raising the precision of diabetes predictions, which could help with early detection and individualized treatment of the disease. The Gated Recurrent Unit algorithms exhibited high accuracy of 95.27%, followed by other methods, while the Artificial Neural Network had the lowest accuracy of 73.84%.*

Keywords- Artificial Neural Network, FeedForward Neural Network, Convolutional Neural Network, Gated Neural Network, Long Short-Term Memory, Recurrent Neural Network.

I. INTRODUCTION

The chronic metabolic disease known as diabetes mellitus is typified by an inability to control blood sugar levels because of a malfunction in the generation or action of insulin. A major public health concern is the prevalence of diabetes, particularly type 2 diabetes mellitus (T2DM), which is estimated to impact 463 million individuals globally as of 2019 and is predicted to increase to 700 million by 2045. Approximately 90% of all occurrences of diabetes are type 2, which is frequently linked to lifestyle factors like obesity, poor food, and inactivity. Severe complications, such as cardiovascular disease, renal failure, blindness, and neuropathy, can result from untreated type 2 diabetes. Therefore, it is crucial to diagnose and treat type 2 diabetes early in order to enhance patient outcomes and lower medical expenses.

The fasting plasma glucose test and the HbA1c test are two traditional diagnostic techniques for type 2 diabetes that offer useful information, but they frequently involve invasive procedures and may not be sensitive enough to identify the disease in its early stages. The potential to improve predictive models and offer non-invasive, affordable tools for T2DM diagnosis and management is presented by developments in machine learning and deep learning. By using enormous volumes of clinical and patient data, these computational methods are able to accurately forecast the risk of diabetes, enabling earlier intervention and more individualized care.

Support vector machines, decision trees, and random forests are examples of machine learning (ML) algorithms that have demonstrated encouraging outcomes in the prediction of type 2 diabetes by examining important risk factors like age, blood pressure, BMI, and glucose levels. More recently, complex, high-dimensional datasets such as electronic health records (EHRs), time-series health data, and retinal pictures have been analyzed using deep learning (DL) models. Advanced deep learning (DL) architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have shown great accuracy in disease prediction, particularly when pattern recognition from sequential data or images is required.

Specifically, hybrid deep learning models and ensemble methods have been suggested as ways to get around the drawbacks of conventional machine learning. For instance, the temporal dependencies in time-series health data are addressed by the use of Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTMs), which over time enable more precise predictions. Real-time monitoring of patients at risk is made easier by these recurrent models, which identify patterns of diabetes progression by capturing both short-term and long-term dependencies in patient health data.

This study compares the effectiveness of several machine learning and deep learning methods for predicting type 2 diabetes. The accuracy, precision, recall, and F1 score of a number of models—including Artificial Neural Networks (ANNs), Feedforward Neural Networks (FNNs), CNNs, GRUs, LSTMs, and RNNs—are assessed in this study using a large dataset of patients with type 2 diabetes. This study intends to determine the best prediction methods for boosting clinical decision-making and early diabetes diagnosis by offering a thorough examination of various models.

Recent developments in data science and computational techniques have created new opportunities for the early identification of diabetes. Two potent technologies that can analyze intricate, high-dimensional healthcare datasets to find patterns and generate precise predictions are machine learning (ML) and deep learning (DL). Using machine learning algorithms to predict T2DM can provide non-invasive, affordable alternatives to established diagnostic techniques while reducing reliance on them. To precisely predict the chance of developing diabetes, these predictive models examine a range of risk factors, such as health history, genetic predisposition, lifestyle indicators, lab test findings, and patient demographics.

Overall, the paper underscores the urgency of addressing the growing diabetes epidemic and highlights the potential of ML algorithms in improving early detection and management of the disease. Through comprehensive analysis and evaluation, the study attempts to support the advancement of more accurate and efficient predictive models for diabetes mellitus, ultimately benefiting patients, healthcare providers, and health systems alike.

II. LITERATURE REVIEW

Christian Wachinger, Tom Nuno Wolf et al. [1] Using 3D neural networks and a sizable dataset from the UK Burbank, this study assesses the automatic detection of type 2 diabetes from neck-to-knee MRI images. Finding the optimal MRI contrast stations and combinations for diabetes prediction is the aim, along with assessing the advantages of including clinical risk factors in the model. Using MRI scans from 3,406 subjects—half of whom had diabetes—five-fold cross-validation was used to train and validate the deep learning model. Using data from several MRI stations, the ensemble model produced a balanced accuracy of 78.7%, surpassing predictions made using only quantitative fat measurements. This method may be used in addition to more conventional diagnostic techniques for non-invasive, affordable diabetes screening and monitoring using MRI.

Yechan Han, Dae-Yeon Kim et al. [2] Glu-Ensemble, a deep learning framework for precise blood glucose prediction in patients with type 2 diabetes (T2DM), is presented in this paper. It allows for instant predictions for new patients by addressing the drawbacks of conventional models, such as small sample sizes, poor data quality, and the requirement for initial calibration. Glu-Ensemble decreases bias and increases generalizability by employing a cohesive strategy and an ensemble of predictive models. Metrics like error grid analysis and root mean square error show that the model outperformed traditional techniques in terms of accuracy when tested on a sizable dataset. This approach has the potential to improve patient decision-making about insulin, nutrition, and exercise in clinical blood glucose management.

Jingcheng Hu, Guangyu Hao et al. [3] This study examines how patients with type 2 diabetes mellitus (T2DM) might be predicted to have obstructive and hemodynamically severe coronary artery disease (CAD) using a deep learning-based coronary artery calcium score (DL-CACS). Using a completely automated DL approach for CACS, the severity of CAD was evaluated in T2DM patients, who frequently had significant arterial calcification. AUCs of 0.753 and 0.769, respectively, showed that DL-CACS was a very accurate predictor of hemodynamically significant CAD (fractional flow reserve ≤0.8) and obstructive CAD (≥50% stenosis) in a group of 469 individuals. With a far shorter analysis time than manual scoring, DL-CACS provided a quicker, more dependable option that could enhance CAD risk assessment and management in type 2 diabetes.

Enrico Manzini, Bogdan Vlacho et al. [4] This review of the literature describes new developments in diabetes clustering and classification, emphasizing a move toward more in-depth, data-driven analysis. Five different T2DM clusters were proposed by Ahlqvist et al.'s study based on diagnostic factors; nevertheless, cluster stability over time is still an issue. Autoencoders and unsupervised feature learning are two deep learning techniques that have shown promise for disease prediction and patient clustering, especially when examining electronic health records (EHRs). But there are drawbacks to the present T2DM classification and the use of tailored therapy, including the dependence on single time-point data, a limited diagnostic focus, and interpretability problems. These advancements highlight the value of tailored, long-term strategies in the treatment of type 2 diabetes.

Bala Manoj Kumar P,Srinivasa Perumal R et al. [5] The progression of diabetes detection and classification techniques from conventional algorithms to sophisticated machine learning and deep learning models is traced in this overview of the literature. Early research included prediction techniques such as the ADAP algorithm and expert systems, but more recent research has examined a variety of machine learning approaches, such as random forests, naive Bayes, and neural networks, with considerable gains in accuracy. With accuracies as high as 98%, performance has been further enhanced by deep learning techniques and hybrid models, such as genetic algorithms and neural networks. In order to forecast diabetes more accurately and consistently, recent advancements have centered on merging models and improving feature selection.

Kannadasan K, Damodar Reddy Edla et al. [6] The improvements in diabetes categorization, especially with deep learning models, are highlighted in this review of the research. To diagnose diabetes, a number of earlier studies used techniques like expert systems, electronic nose-based neural networks, and ensemble modeling. Important references highlight the function of deep learning, which has uses in Type 2 diabetes prediction, diabetic retinopathy detection, and more general medical diagnosis. The authors highlight recent research on autoencoders utilized in a variety of domains and cite seminal publications on neural networks and optimization strategies. The authors' suggested deep neural network framework for diabetes categorization using stacked autoencoders is supported by this background.

Swapna G, Vinayakumar R et al. [7] The development of deep learning techniques for non-invasive diabetes detection from conventional machine learning techniques is described in this overview of the literature. Early methods, which struggled with high-dimensional data, depended on feature extraction and selection, with different degrees of accuracy. With accuracies comparable to the finest conventional techniques, deep learning has since become a potent substitute. Diabetic autonomic neuropathy has been found to impact heart rate variability (HRV) signals, which are a useful non-invasive indicator for diabetes identification. This background lends credence to the move toward deep learning for improved diabetes detection accuracy with HRV signals.

Firoozeh Mostafavi-Darani Fereshteh Zamani Alavijeh et al. [8] The prevalence and financial burden of type 2 diabetes (T2D), a growing worldwide concern, are highlighted in this review of the literature. In 2013, 382 million adults worldwide suffered from diabetes; by 2035, that number is predicted to rise to 592 million, with type 2 diabetes being the most common. The anticipated prevalence of type 2 diabetes in Iran was 8.6%, and the number of patients is expected to increase significantly, adding significantly to the country's financial burden. Self-care, which emphasizes nutrition, exercise, and medication adherence, is crucial for effective T2D control. Nonetheless, there are many obstacles to dietary compliance, influenced by social, interpersonal, and personal factors, and non-compliance rates vary greatly. This review emphasizes the necessity for methods to increase patient compliance and stresses the vital significance of dietary adherence.

Huaping Zhou, Raushan Myrzashova et al. [9] Deep learning methods are increasingly being used in healthcare, particularly for diabetes classification and prediction, as this literature review demonstrates. Deep learning has shown successful in the analysis of complicated data, including CGM signals, medical imaging, and electronic health records. Convolutional neural networks (CNNs), deep neural networks, and hybrid models have all been used in several research to increase the accuracy of diabetes prediction. This research attempts to improve prediction by using a DNN-based model (DLPD) to evaluate diabetes risk and distinguish between kinds, improving early identification and individualized care, whereas current models mostly concentrate on predicting the presence of diabetes.

Choi, E, Bahadori, M. T, Schuetz et al. [10] The limits of current disease progression modeling techniques are described in this review of the literature. For conditions like diabetes and Alzheimer's, specific-purpose models depend on domain expertise, but general-purpose models tackle scalability issues while covering a wider spectrum. Computational difficulties and inefficiencies plague multilabel event modeling techniques like discretization and continuous-time models. The majority of recent deep learning models for EHR data, such as phenotypic and representation learning research, have concentrated on specific prediction tasks. A need for generalizable, scalable models that can forecast various outcomes without requiring domain-specific knowledge is highlighted by this background, and this is exactly what Doctor AI aims to address.

III. METHODOLOGY

3.1 Dataset

Dataset collected from the Kaggle website. The Type 2 diabetes prediction dataset comprises 952 entries with 18 features that provide a comprehensive profile of individuals, including both numerical and categorical data. The numerical columns are BMI, Sleep, SoundSleep, and Pregnancies, although some of these have missing values. The dataset includes categorical features such as Age, which records the age group (e.g., "50-59"), and Gender (Male or Female). Family health history is represented by Family_Diabetes, indicating whether diabetes runs in the family, while highBP denotes the presence of high blood pressure.

Lifestyle factors like PhysicallyActive (level of physical activity), Smoking, Alcohol use, and JunkFood consumption are also included. Medical and well-being metrics include the BPLevel (e.g., "normal" or "high"), RegularMedicine (whether the individual takes regular medication), and Stress levels. Additionally, Pdiabetes indicates pre-diabetes status, and UriationFreq reflects the frequency of urination (e.g., "not much"). The target variable, Diabetes, shows whether an individual has diabetes. Notably, the dataset contains some missing values in the BMI, Pregnancies, and Diabetes columns. Overall, this dataset, with its mix of demographic, medical, and lifestyle features, is rich in information for developing machine learning models aimed at predicting diabetes, though preprocessing will be needed to handle categorical data and fill missing values.

Dataset URL:
https://www.kaggle.com/datasets/tigganeha4/diabetes-dataset-2019

Fig.1 outlines the key steps in a model workflow, from data collection to model evaluation and results interpretation.

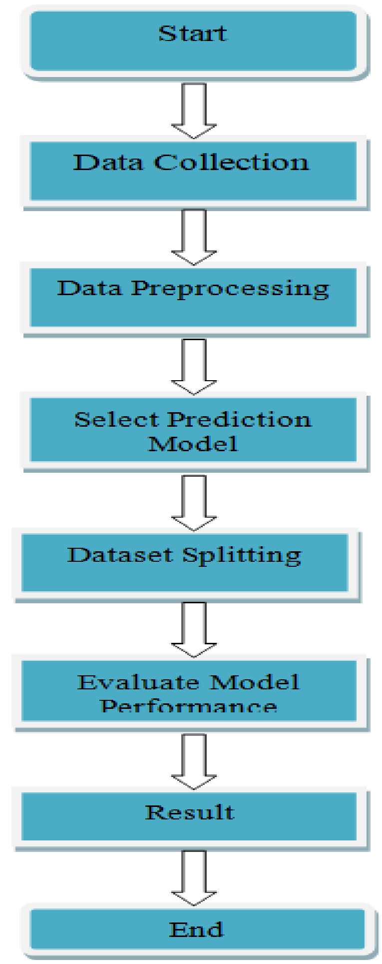

Fig 1 Workflow of diabetes prediction

3.2 Data Preprocessing

To effectively use machine learning for type 2 diabetes management, data preparation is an essential first step. To guarantee accuracy and dependability in prediction models, the data must be cleaned and prepared. In the case of type 2 diabetes, this procedure usually starts with gathering pertinent information on blood sugar levels, insulin sensitivity, eating patterns, and physical activity. Dealing with missing numbers, outliers, and inconsistencies is the first phase in the data cleansing process. Mean substitution and predictive modelling are two techniques that can be used to impute missing data. Clinical judgement may be used to eliminate or modify outliers, which have the potential to distort results. Feature engineering is then used to take the raw data and turn it into useful information. This can involve adding new features or altering current ones in order to more accurately depict the underlying patterns

IV. PREDICTION TECHNIQUES FOR TYPE 2 DIABETES

a) Artificial Neural Network

Artificial Neural Networks (ANNs) are widely used to predict Type 2 diabetes because of their capacity to identify intricate correlations in huge datasets. Multi-layer perceptrons (MLPs), in particular, are ANNs that can assess a variety of parameters, including blood pressure, age, and BMI, to find patterns associated with the risk of Type 2 diabetes. An Introduction to ANN for Diabetes Prediction The input, hidden, and output layers of an artificial neural network (ANN) are made up of interconnected neurons.The ANN uses hidden layers to process patient data (such as age, BMI, and glucose level) and outputs the prediction (such as whether the patient has Type 2 diabetes or not).Artificial neural networks (ANNs) provide a useful model for diabetes prediction by learning intricate, nonlinear correlations between input features.

y=f(∑i=1nwixi+b) [1]

Where xi = input features, wi = weights corresponding to each input, b = bias term, f = activation function (e.g., ReLU, sigmoid, tanh), y = output of the neuron.

Weighted Sum: The inputs xi are multiplied by their corresponding weights wi and summed up.

Bias: The bias term b shifts the activation function to improve the model's flexibility.

Activation Function: f applies non-linearity to the output, allowing the network to learn complex relationships.

b) Feedforward Neural Network

The Feedforward Neural Network (FNN) is a widely utilized deep learning model for Type 2 diabetes prediction because of its ease of use and efficiency. Data moves from the input layer to the output layer in a single direction via one or more hidden layers in FNNs.

Feedforward Neural Network (FNN) follows a structure similar to a basic ANN but is explicitly defined by data flow in one direction, from input to output, without any cycles.

yj=f(∑i=1nwijxi+bj) [2]

Where xi = input features to the layer, wij = weight connecting input i to the neuron j in the current layer, bj = bias for neuron j, f = activation function (e.g., ReLU, sigmoid, tanh), yj = output of neuron j.

c) Convolutional Neural Network

CNNs are perfect for complicated pattern identification because, in contrast to standard neural networks, they automatically extract spatial characteristics from data using convolutional layers. Patient data, such as sequential health data or medical imaging, are sent into the network to forecast diabetes. Pooling layers lower dimensionality to capture only the most critical characteristics, while convolutional layers detect key patterns (such as retinal changes or heart rate variability). Ultimately, these features are combined for classification by fully linked layers, which produce a diabetes risk prediction.

A Convolutional Neural Network (CNN) is primarily designed to process grid-like data, such as images, using convolutional layers to detect patterns and features at various levels. CNNs use mathematical operations like convolution, pooling, and activation to learn spatial hierarchies of features.

$$f(i,j) = \sum m \sum n\ Wm,n.\ x(i + m,j + n) + b \qquad [3]$$

Where, $f(i,j)$ is the output feature at location (i,j), W is the filter matrix, $x(i + m,j + n)$ are the input values within the filter region, b is the bias. A pooling layer, commonly max pooling, follows to reduce the feature map’s dimensions while retaining key features, typically by taking the maximum value in each small region, as in:

$$p(i,j) = maxpoolf(i + m,j + n) \qquad [4]$$

Finally, the feature maps pass through fully connected layers, which generate the network's final output. In time series applications, CNNs can successfully predict values by learning temporal dependencies in the data.

d) Gated Recurrent Unit (GRU)

A particular kind of Recurrent Neural Network (RNN) called a Gated Recurrent Unit (GRU) is very helpful for forecasting Type 2 diabetes when dealing with sequential or time-series data, including patient monitoring data (e.g., glucose levels, heart rate, or insulin usage over time). Because GRUs are built to capture temporal dependencies in data, they are perfect for modeling changes in health measurements or the course of diabetes.

The Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) that addresses the vanishing gradient problem often found in traditional RNNs by using gates to control information flow. It is simpler than the LSTM (Long Short-Term Memory) network and requires fewer parameters. GRUs are popular for sequence modeling tasks, like time series analysis and natural language processing, due to their efficiency and effectiveness in capturing dependencies.

Reset gate

$$rt=\sigma(Wr\cdot[ht-1,xt]+br) \quad [5]$$

Update gate

$$zt=\sigma(Wz\cdot[ht-1,xt]+bz) \quad [6]$$

Candidate Hidden State

$$h\sim t=\tanh(Wh\cdot[rt\odot ht-1,xt]+bh) \quad [7]$$

Hidden State Update

$$ht=(1-zt)\odot ht-1+zt\odot h\sim t \quad [8]$$

e) Long Short-Term Memory (LSTM)

Predicting form 2 diabetes is a good use case for Long Short-Term Memory (LSTM) networks, a form of Recurrent Neural Network (RNN), especially when dealing with time-series or sequential health data like heart rate, insulin use, and glucose levels over time. Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. They achieve this by using a unique architecture with three main gates: the forget gate, the input gate, and the output gate. These gates control the flow of information, allowing the LSTM to decide what to remember and what to forget.

$$it=\sigma g\ (Wixt+Uiht-1+bi) \quad [9]$$
$$Ct'=\sigma c(Wcxt+Ucht-1+bc) \quad [10]$$
$$Ct=ft\ xCt-1+itxCt' \quad [11]$$
$$ot=\sigma g(Woxt+Uoht-1+bo) \quad [12]$$
$$ht=ot*\tanh(Ct) \quad [13]$$

f) Recurrent Neural Networks (RNN)

A Recurrent Neural Network (RNN) is a type of neural network designed for sequential data, such as time series or language, by utilizing connections that loop back to previous layers, creating a form of memory. This structure enables RNNs to retain information from earlier steps, making them suitable for tasks where context across time is essential. At each time step t, the hidden state $ht$is calculated based on the current input xt and the hidden state from the previous time step $ht-1$ as follows:

$$ht=f(Whxt+Uhht-1+bh) \quad [14]$$

where $ht$is the hidden state at time t, $xt$is the current input, Wh and Uh are weights, and bh is a bias term.The activation function f (e.g., tanh or Relu) introduces non-linearity. This recurrent connection allows RNNs to recognize temporal patterns, but traditional RNNs can struggle with long sequences due to issues like vanishing gradients. Advanced RNN types, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), address this by adding mechanisms to retain or forget information over longer sequences. Fig.4 shows a visual comparison of actual vs. predicted prices was plotted.

V. COMPARITIVE ANALYSIS

i. Dataset

The dataset used in the analysis is taken from an online resources. It has 952 rows of data and 18 columns of attributes. The dataset is of type 2 diabetes dataset.

ii. Evaluation Metrics

The evaluation metrics are used to assess the performance or effectiveness of a model. The evaluation metrics used are as follows.

1. Accuracy

Accuracy quantifies the percentage of accurate predictions out of the total predictions made.

Accuracy = (TP+TN)/(TP+TN+FP+FN) [15]

2. Precision

Precision calculates the percentage of accurate positive forecasts out of all positive predictions are made.

Precision = TP/(TP+FP) [16]

3. Recall

Recall quantifies the percentage of true positive predictions out of all actual positive instances.

Recall = TP/(TP+FN) [17]

4. F1 Score

F1 Score is the harmonic mean of precision and recall, providing a balance between the two metrics.

F1 score = (2×Precision×Recall)/(Precision + Recall) [18]

VI. RESULT AND DISCUSSION

The diverse algorithms are used on the dataset. Based on The metrics for assessment the way in which the algorithms are known and compared. The results of the evaluation metrics of all the algorithms are shown in the Table 1. The overall comparison results are given below.

Algorithms	**Accuracy**	***Precision***	***Recall***	***F1Score***
• Artificial Neural Network	87.99%	0.93%	0.80%	0.86%
Feedforward Neural Network	93.09%	0.83%	0.96%	0.89%
• Convolutional Neural Network	94.54%	0.91 %	0.99%	0.95%
Gated Recurrent Unit	95.27%	0.94%	0.97%	0.91%
Long Short-Term Memory	93.09%	0.92%	0.95%	0.93%
Recurrent Neural Networks	0.88%	0.84%	0.94%	0.89%

Table 1.Overall Comparision

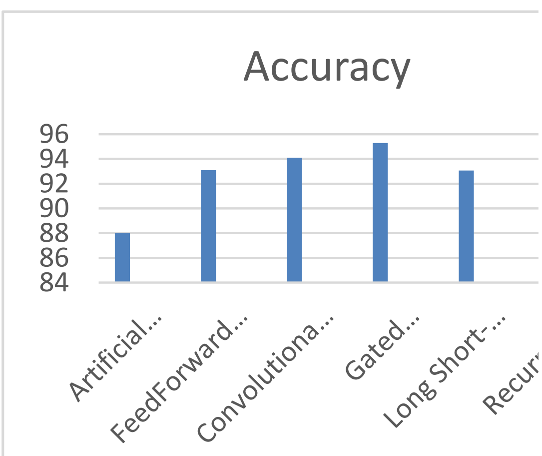

Fig. 1 Accuracy of Different Algorithms

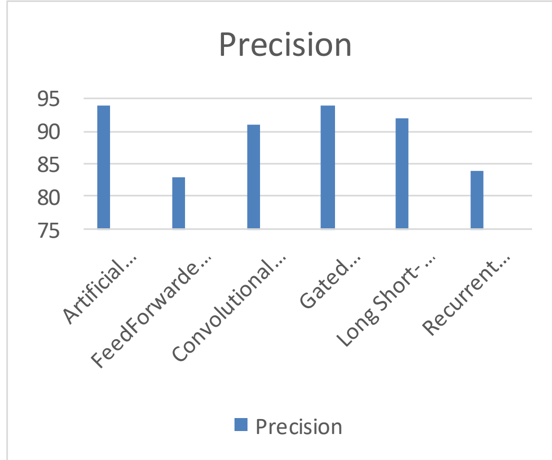

Fig. 2 Precision of Different Algorithms

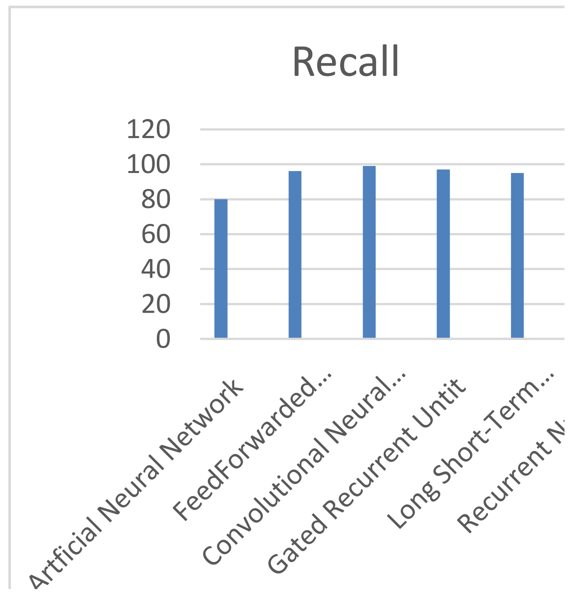

Fig. 3 Recall of Different Algorithms

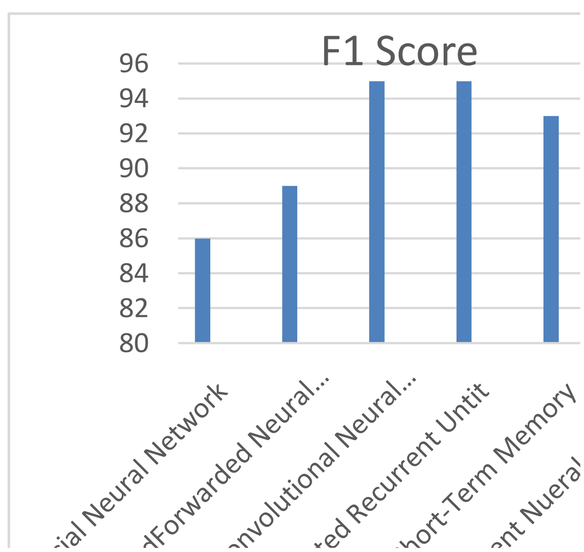

Fig. 4 F1 Score of Different Algorithms

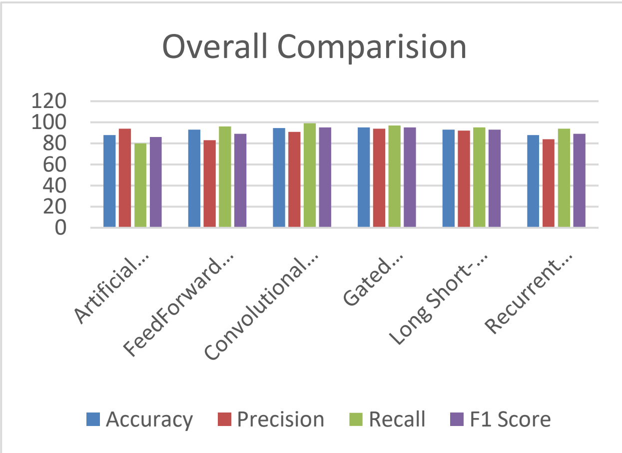

Fig. 5 Overall Comparision of Different Algorithms

The implementation of the algorithm is done in the Google Colab. Diverse algorithms are used on the dataset Based on the evaluation matrices of all algorithms are shown in Table.1. According on the findings, The Gated Recurrent Unit has the highest accuracy of 95.27% and The Artificial Neural Network has the lowest accuracy of 87.99%. The Gated Recurrent unit has the highest precision of 94% and the Feedforward Neural Network has the lowest precision of 83%. The Convolutional Neural Network has the highest recall of 99% and the Artificial Neural Network has the lowest precision of 80%. The Convolutional Neural Network has the highest F1 score of 95% and the Artificial Neural Network has the lowest F1 score of 86%.

VII. CONCLUSION

By analyzing amount of data, these algorithms are able to forecast the results of specific patients, direct treatment plans, and improve the management of diseases in general. In this study multiple deep learning models, including Artificial Neural Networks (ANN), Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), and Long Short-Term Memory networks (LSTM) for the task of Type 2 Diabetes prediction. Improved glycemic control, fewer problems, and ultimately a higher quality of life can result from healthcare providers customizing therapies to meet the specific needs of each patient by utilizing sophisticated computational tools. It's crucial to recognize that additional research is necessary to improve these models, confirm their efficacy in practical contexts, and handle any potential ethical and privacy issues. With sustained technological progress and cooperation among researchers, physicians, and patients, machine learning can be used to control type 2 diabetes and revolutionize the way healthcare is provided. Metrics like accuracy, precision, recall, and F1 score were used to assess the models on a dataset of 952 patient records with 18 attributes. According to the report, The best accuracy, 95.27%, was attained by GRU. CNN received the highest F1 score (95%) and the best recall (99%). **ANN** had the lowest overall performance (accuracy of 87.99%).

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