

A novel method for prediction of diabetes mellitus using deep convolutional neural network and long short-term memory

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ABSTRACT

Hyperglycemia arises due to diabetes mellitus, which is a persistent and life-threatening ailment. In this paper deep convolution neural network can be embedded to long short-term memory networks to recognize early prediction of diabetes and to decrease the complications that can be occurred through diabetes irrespective to the age. Diabetes problem is being gradually growing and presently, it is reported as a significant cause of death in the top spot. According to the recent studies 48% of overall world population will be affected by diabetes by 2045. If diabetes unidentified in early stages, it may cause other additional cardiac problems. In the proposed based work, a deep learning framework deep combination of convolution neural network and long short-term memory is proposed by embedding both to leverage their respective advantages for diabetes recognition and to allow early prediction of diabetes to avoid other complications. The experimental evolution on the bunch mark of diabetes data set demonstrates the proposed model embedded deep long short-term memory outperforms other machine learning and conventional deep learning approaches. The proposed algorithm in this paper outperforms existing techniques and evaluates total effectiveness and accuracy of predicting whether a person will suffer from diabetes.

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1. INTRODUCTION

Now a days, health related issues are increasing rapidly which are considered as the major cause of mortality and various other complications. These complications lead towards several severe issues such as lung cancer, Alzheimer, heart related diseases and diabetes. Currently, diabetes is one of the major reasons for mortality in various countries. Diabetes is known as the main cause of several serious health condition such as heart stroke, nervous system, eye problem, and kidney problems [1]. 9.4% of the total population of United States are suffering from the diabetes which accounts around 30.3 million people [2]. Similarly, 10% of population i.e., 98 million people in China are affected due to diabetes. The official statistics has approximated that by the year of 2045, 9.9% of population globally would be affected due to diabetes [3]. In current scenario, rate of diabetes patients is increasing steadily, and it is considered as the main challenge for

health-related community globally. The impact of diabetes is increasing rapidly, and it was as the seventh main reason for death in 2016 as reported by world health organization (WHO) [4].

Diabetes patient can maintain a normal life with the help of appropriate diagnosis and treatments. Several health parameters measurements are used by clinicians to identify the diabetes which include random blood glucose, A1c, fasting blood glucose and oral glucose tolerance. Based on these tests, the type of diabetes can be identified, and patients can check and record their glucose levels to maintain the proper balance. According to Rahman *et al.* [5] suggested that combination of body mass index (BMI), blood pressure, glucose, diabetes pedigree function, age, thickening of skin, pregnancy and insulin can be considered as an efficient solution to identify the diabetes. According to Aravamudu *et al.* [6] compared and analysed data is processed by different machine learning algorithms such as random forest (RF), support vector machine (SVM), Naive Bayes classifier, H2O AutoML, convolutional neural network (CNN), long short memory neural network (LSTM) for the classification. It is observed and understood that the LSTM provides a better classification efficiency of 98% and the H2O AutoML method giving the least efficiency of 75%.

Now a days, data mining machine learning based schemes have gained good attention in bio-medical field. These methods are popularly employed in diverse real-time medical applications such as electrocardiogram (ECG) signal processing, X-Ray image processing, tumor detection and diabetes classification. Here, we focus on the diabetes classification using machine learning (ML) algorithms. Recently, ML based methods are widely adopted in diabetes prediction such as SVM, decision tree (DT), random forest, AdaBoost, logistic regression (LR) and artificial neural network (ANN). Moreover, dimensionality reduction and feature extraction techniques are also incorporated to improve the classification performance. Jaya and Sam [7] proposed effective and efficient multimodal biometric system using CNN which helps to predict identity of a individual based on his/her iris pattern.

Similarly, deep learning-based schemes have reported the better performance for classification when compared with other machine learning techniques. Hasan *et al.* [8] developed a deep neural network (DNN) based approach for type-2 diabetes, enhanced DNN [9], [10]. In [11], authors presented genetic algorithm-based model for feature selection and extreme learning machine (ELM) neural network model to efficiently classify diabetes. But still, the deep learning schemes face several challenging issues.

Remaining article is organized as: next section presents a brief literature review about deep learning based techniques for diabetes classification. Section 2 describes the proposed CNN and LSTM based combined model. Section 3 describes the experimental analysis and comparative study. Finally, section 4 concludes the research with some observations.

2. BACKGROUND WORK

As discussed before, the deep learning based methods are widely embraced for data mining applications. Hence, in this section we present the brief literature review about deep learning based existing techniques for diabetes classification. A scheme which uses data pre-processing, data shuffling and supervised classification which includes decision tree, ANN, Naïve Bayes (NB) and DL [12]. The experimentation evaluation demonstrates that the deep learning scheme attains better classification efficacy.

According to Swapna *et al.* [13] used ECG signal to analyze the heart activities and extracted RR intervals to heart rate variability analysis. The RR interval is used to classify the normal and diabetic signal using deep learning architecture. Authors presented a combined model of CNN and LSTM to extract the temporal dynamic features of HRV data. The captured features are then classified using SVM.

Convolutional long short-term memory technique for classification of disease. This classification model uses CNN, Traditional LSTM, and CNN-LSTM for classification [14]. Prior to this, Boruta algorithm is used for feature extraction which provided glucose, BMI, blood pressure, age and insulin as the significant features which can help to improve the classification performance.

An experimental review study which incorporates outlier rejection, missing value imputation, data sampling, attribute selection, K-fold cross validation and machine learning algorithms for classifying diabetes through data mining methods [15]. Their ML schemes employ algorithms such as NN, DT, RF, AdaBoost, Naïve Bayes, and multilayer perceptron (MLP). A novel scheme to forecast the diabetes and its occurrence through data mining techniques using deep learning. Generally, the diabetes is grouped as type-1 and type-2 which have different treatment methods according to their stages of severity. Hence, this method presents a technique to identify the suitable treatment method [16]. Mishra *et al.* [17] focused on the diagnosis of type-2 diabetes and developed a hybrid optimization scheme called as enhanced and adaptive genetic algorithm (EAGA). This scheme uses readings of symptoms and presents a model to measure the occurrence of diabetes for forecasting. A multilayer perceptron (MLP) model is used for classification of the diabetes patterns based on their symptoms. To do this, this task is transformed into the classification problem and introduced a DNN, which uses dropout regularization to deal with overfitting. During the learning process,

several parameters are tuned, and binary cross-entropy loss function is utilized to improve the accuracy by reducing the training error. Like this approach, Ashiquzzaman *et al.* [18] also focused on the overfitting issue of deep learning and presented a new deep learning architecture which uses fully connected layer and dropout layer. Gadekallu and Khare [19] presented a model for the classification of the heart and diabetes disease and presented cuckoo search roughest based attribute selection using fuzzy logic system. The optimization scheme minimizes the algorithmic complexity, also the efficient designing of fuzzy rules helps to improve the classification performance. Padmaja *et al.* [20] reported that machine learning algorithm is combined with clustering to find estimation of effort. Thus, data pre-processing is considered as an important part. In this work, a selective data processing scheme is introduced which incorporate the outlier information into the subset to obtain the even distribution of features [21], [22]. Later, synthetic minority oversampling technique (SMOTE) scheme is used to balance the training process while controlling the effects of outliers. The blood glucose level is the important aspect in diabetes where continuous monitoring of glucose level can improve the quality of life. Nnamoko and Korkontzelos [23] focused on this scheme and considered neural network based automated approach for monitoring these levels for type -1 diabetes patients. Sailasya *et al.* [24] proposed a analyzing the performance of stroke prediction using ML classification algorithms moreover, supervised back propagation is applied on the training dataset to fine tune the network. Finally, softmax layer classifies the data corresponding to their classes.

Paul and Choubey [25] introduced a twofold scheme for diabetes classification where the first stage develops genetic algorithm model for feature selection which reduces dimension from 8 to 4. In next stage, radial basis function neural network (RBF NN) model is implemented for classification of the final attribute set. Krishnaiah and Kadegowda [26] introduced a hybrid approach for undergraduate engineering students employment prediction using hybrid approach in machine learning. Panda *et al.* [27] proposed prediction of diabetes disease using machine learning algorithms and concluded K-nearest neighbor (KNN) works well for the dataset includes a large number of datasets that it is easier to minimize processing time. SVM deals with a wide number of functions for the dataset in a better way.

3. PROPOSED METHOD

Here, we introduce the proposed scheme for diabetes forecasting and classification through deep learning technique. Currently, CNN based models have attained huge popularity in machine learning arena, hence, we use CNN model for learning. To improve the efficacy, we incorporate an LSTM model that handles the gradient vanishing problem in DL.

3.1. Convolutional neural network (CNN)

CNN is known as a distinctive category of MLP based ANN. Generally, these networks resemble to neural networks in various aspects such as the main component is neurons with weights and biases that need to be trained upon for pattern analysis. Neurons take input data, and a dot product operation is performed on this input followed by a function of nonlinearity. CNNs are widely used in image processing, video processing and data mining applications where input data is traversed through various learning phases and corresponding final score is obtained at the output end. A basic CNN architecture consists of three main layers which are convolutional layer, pooling layer and fully connected layer. Along with these layers, it requires an activation function rectified linear activation function (ReLU).

In this work, we consider the data vector, which is denoted as $x = (x_1, x_2, \dots, x_{n-1}, x_n, cl)x_n \in R^d$ where x denotes the attribute and cl denotes the class label $cl \in R$. The convolution layer operation generates a feature map as f_m by applying convolution procedure on the input diabetes data with a filter as $w \in R^{f \times f}$ where f is the features. The output of this layer is further fed into the next layer of block of the network. The feature map is obtained from set of features f which can be expressed as:

$$hl_i^{f_m} = \tanh(w^{f_m} x_{i:i+f-1} + b) \quad (1)$$

Here, we apply the filter every feature set i.e. f in the input data given as $\{x_1: f, x_{2:f+1}, \dots, x_{n-f+1}\}$ to produce the feature map i.e. $hl = [hl_1, hl_2, \dots, hl_{n-f+1}]$ and b is bias term as $b \in R$ and $hl \in R^{n-f+1}$. In this work, we use ReLU activation function for convolution layer which applies $\max(0, x)$ to each input x . Further, the convolution layer output is fed to the pooling layer. Here, main aim of pooling layer is performing downsampling on the feature data. We utilize max pooling down sampling operation on every feature map as $\vec{hl} = \max(hl)$. This process helps to obtain the most significant features. The selected features are further processed through the fully connected layer which comprises softmax function. This function provides the probability distribution of features over every class. Thus, the fully

connected layer is considered as the final output layer which generates the classification or prediction results. Figure 1 shows a basic architecture of CNN.

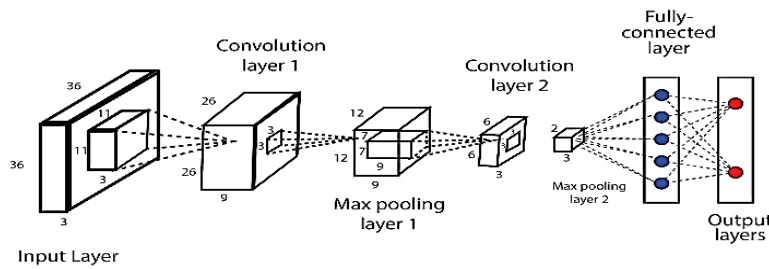


Figure 1. CNN architecture

The combined method was proposed in the Algorithm 1.

Algorithm 1. Deep CNN and LSTM

Consider the data vector denoted as $x = (x_1, x_2, \dots, x_{n-1}, x_n, cl) x_n \in R^d$ where x denotes the attribute and cl denotes the class label $cl \in R$.

Step 1: The convolution layer operation generates a feature map as f_m by applying convolution procedure on the input diabetes data with a filter as $w \in R^{f \times f}$ where f is the features.

Step 2: The output of this layer is further fed into the next layer of block of the network. The feature map is obtained from set of features f which can be expressed as:

$$hl_i^{f_m} = \tanh(w^{f_m} x_{i:i+f-1} + b)$$

Step 3: we apply the filter every feature set i.e. f in the input data given as $\{x_{1:f}, x_{2:f+1}, \dots, x_{n-f+1}\}$ to produce the feature map i.e. $hl = [hl_1, hl_2, hl_3, \dots, hl_{n-f+1}]$, and b is bias term as $b \in R$ and $hl \in R^{n-f+1}$.

Step 4: used ReLU activation function for convolution layer which applies $\max(0, x)$ to each input x . The convolution layer output is fed to the pooling layer. Here, main aim of pooling layer is performing downsampling on the feature data to obtain most significant features.

Step 5: The selected features are further processed through the fully connected layer which comprises SoftMax function. This function provides the probability distribution of features over every class. Thus, the fully connected layer is considered as the final output layer which generates the classification or prediction results.

Step 6: $L = \{L(1), L(2), \dots, L(T)\}$ where $L(T)$ denotes the data of length T . In LSTM, the hidden units are represented by H_t and parameters of LSTM at time t

Step 7: L_t is the input vector for LSTM unit b is the bias vector, I_t denotes the input gate's activation vector at time t , F_t is the forget gate's activation vector at time t , O_t is the output gate's activation vector at time t , C_t denotes the cell state vector, H_t is the hidden state vector at time t , and g is the gating variable.

Step 8: The forget gate F is used to determine that which data from previous cell need to be preserved and output gate O handles the cell states which are presented as outcome as short-term memory H_t . the cell unit is also considered as the recurrent unit which has tanh activation function.

Step 9: The recurrent unit is computed with the help of current input data and state of previous frame H_{t-1} . Finally, weight and bias parameters are applied to obtain the desired output.

Step 10: End

3.2. LSTM network

In this section, we preset a brief overview of LSTM model which is a kind of recurrent neural network (RNN). The conventional RNN model consist of simple RNN unit to learn the data but these units suffer from the issue of gradient vanishing problem. Currently, LSTM is considered as a promising solution to overcome these issues because it uses standard memory blocks to store and process the data. Moreover, LSTM is capable to handle the long terms dependencies of data efficiently. Generally, a memory block in LSTM is a sophisticated processing unit which contains memory cells. Figure 2 depicts the design of LSTM unit.

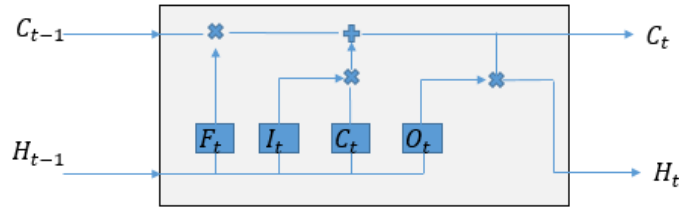


Figure 2. LSTM unit

The input and output gates are constructed using multiplicative gates where information is passed through element-wise multiplication. Let consider an input sequence given as $L = \{L(1), L(2), \dots, L(T)\}$ where $L(T)$ denotes the data of length T. In LSTM, the hidden units are represented by H_t and parameters of LSTM at time t are given as:

$$\begin{aligned}
 I_t &= \sigma \left((L_t + H_{t-1})W^i + b_i \right) \\
 F_t &= \sigma \left((L_t + H_{t-1})W^f + b_f \right) \\
 O_t &= \sigma \left((L_t + H_{t-1})W^o + b_o \right) \\
 g &= \tanh \left((L_t + H_{t-1})W^g + b_g \right) \\
 C_t &= C_{t-1}F_t + gI_t \\
 H_t &= \tanh(C_t)O_t
 \end{aligned}
 \tag{2}$$

where L_t is the input vector for LSTM unit b is the bias vector, I_t denotes the input gate’s activation vector at time t, F_t is the forget gate’s activation vector at time t, O_t is the output gate’s activation vector at time t, C_t denotes the cell state vector, H_t is the hidden state vector at time t, and g is the gating variable.

According to this architecture of LSTM, the input gate I exploits the input data and analyzes that which part of incoming data L_t to be assigned to cell state C . The forget gate F is used to determine that which data from previous cell need to be preserved and output gate O handles the cell states which are presented as outcome as short-term memory H_t . Moreover, the cell unit is also considered as the recurrent unit which has \tanh activation function. The recurrent unit is computed with the help of current input data and state of previous frame H_{t-1} . Finally, weight and bias parameters are applied to obtain the desired output. Figure 3 depicts the structure of LSTM model used for classification of diabetes data.

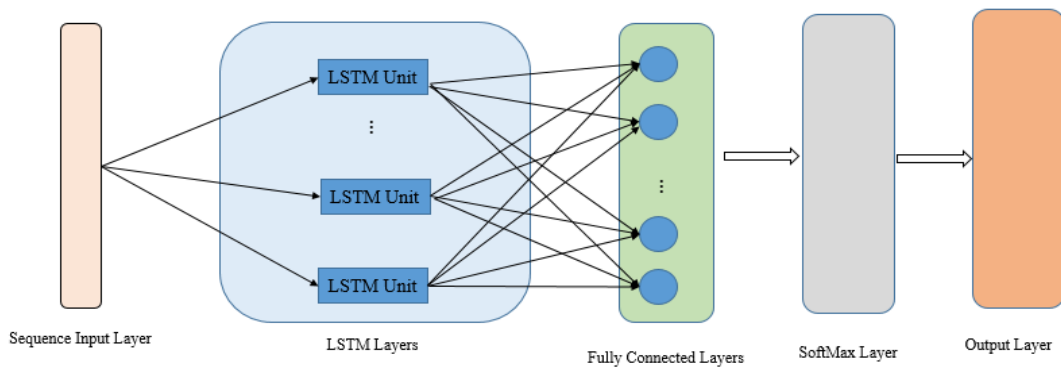


Figure 3. LSTM architecture

4. RESULTS AND DISCUSSION

This part of paper demonstrates the complete experimentation evaluation of presented technique and evaluates its diabetes classification performance against the existing techniques. The presented technique is simulated using MATLAB toolkit that runs on windows operating system (OS). Experimentation system has 8 GB RAM, 1 TB hard drive and Intel i3 processor. This scheme is tested on publically available PIMA Indian diabetes database. This database has 8 attributes and total 768 samples. Table 1 demonstrates the attribute details of PIMA Indian diabetes dataset.

Table 1. PIMA Indian diabetes dataset details

ID	Attribute	Range
1	Pregnancy count	0-9
2	Plasma glucose concentration	0-199
3	Diastolic blood pressure (mm Hg)	0-122
4	Triceps skin fold thickness (mm)	0-99
5	2 – h serum insulin (µU/ml)	0-846
6	Body mass index (kg/ m2)	0-67.1
7	Diabetes pedigree function	0.078-2.42
8	Age (Years)	21-81
9	Output Class	Diabetes/Non-Diabetes

To measure the efficacy of proposed solution, we use confusion matrix, which is obtained based on the classification outcome of proposed model. Table 2 demonstrates the confusion matrix that contains true positive (TP), false positive (FP), true negative (TN) and false negative (FN).

Table 2. Confusion matrix

Actual class	Predicted class	
	Healthy	Diabetes
Healthy	TP	FN
Diabetes	FP	TN

By making use of above-mentioned confusion matrix, we can compute several performance measurement parameters such as accuracy, precision, specificity, sensitivity and F-measure of our presented solution. Accuracy is a unit of measurement for the rate of accurate categorization, and it is represented by the letter *Acc*. It is calculated by dividing the overall no. of accurate predictions by the total no. of correct predictions. It is written as (3):

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

The sensitivity function of the model is one more computation method to assess the performance. This is a calculation of the *TP* rate that is done by recognizing the accurately categorized non-diabetes modules. This may be stated as shown in (4):

$$Sensitivity = \frac{TP}{TP+FN} \tag{4}$$

The *TN* rate that represents the measure of correctly identified Diabetes software modules, is the next performance evaluation metric and may be represented as shown in (5):

$$Specificity = \frac{TN}{TN+FP} \tag{5}$$

The precision of the suggested technique is then computed. It's calculated by dividing the number of *TP* by the sum of *+FP*.

$$P = \frac{TP}{TP+FP} \tag{6}$$

Lastly, the F-measure that is the average of accuracy and sensitivity performance, is calculated. It's written like this:

$$F = \frac{2*P*Sensitivity}{P+Sensitivity} \tag{7}$$

Further, we contrast the efficacy of presented technique with existing techniques in accuracy parameter as mentioned in [2]. This experiment is conducted by dividing the whole data as 70% train data in addition to 30% test data. Table 3 demonstrates the comparative analysis.

Table 3. Comparative analysis

Technique	Accuracy	Evaluation process
ANN-SVM-K - NN-QDA-LDA	79.98%	Random Train-Test
GPC-NB-QDA-LDA	82.01%	10-fold
ANFIS	89.39%	10-fold
K-Means - C4.5	92.40%	10-fold
K-Means	95.38%	10-fold
Decision Tree	95.99%	Random Train-Test
Multi-layer Feed Forward Network	97.97%	Random Train-Test
GA + ELM	98.92%	Random Train-Test
DNN Classifier	97.95%	80:20
DNN Classifier	98.01%	60:40
DNN Classifier	95.98%	10-fold
DNN Classifier	98.61%	70:30
Deep CNN LSTM(Proposed)	99.12%	70:30

Similarly, we measure the performance in terms of sensitivity and specificity as depicted in Figure 4. In this figure we have considered three different scenarios of different training and testing ratios such as 80-20%, 70-30% and 60-40%. The existing scheme obtained the classification accuracy as 98, 97.54, and 98.16 for above mentioned train-test scenario whereas proposed approach reported accuracy for this scenario as 99.18, 99.12, and 98.63. The average accuracy using existing technique is obtained as 97.9 and proposed approach achieves 98.97 % accuracy.

Similarly, we compared the accuracy performance with existing techniques as mentioned in [2] where deep learning obtained the highest accuracy as 98.07% but the proposed approach outperforms by minimizing the misclassifications and training loss. The comparison analysis with various approaches is shown in Table 4. Figure 5 illustrates the comparative analysis with existing approaches [1] in the criteria like accuracy, precision, recall and f-measure.

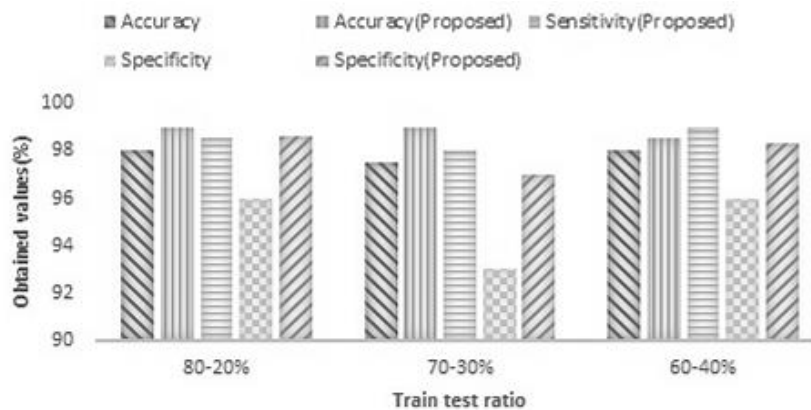


Figure 4. Comparative analysis

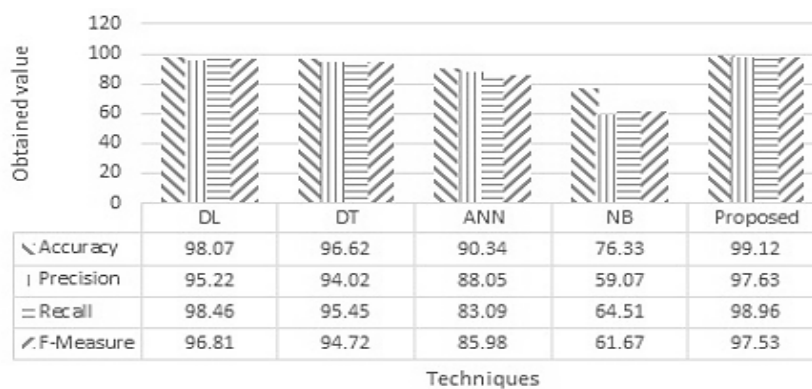


Figure 5. Comparative analysis using different classifiers

Table 4. Classification accuracy comparison

Technique	Accuracy
Firefly and Cuckoo Search Algorithm (CSA)	81%
Feedforward NN	82%
Naïve Bayes (NB)	79.56%
Support Vector Machine (SVM)	78%
LDA – MWSVM	89.74%
Neural Network (NN) with Genetic Algorithm (GA)	87.46%
K-means and DT	90.03%
PCA, K-Means Algorithm	72%
Deep Learning (DL)	98.07
Deep CNN LSTM(Proposed)	99.12

This study shows that the deep learning schemes outperforms when evaluated against conventional classification methods like DT, NB, and ANN. In previous sections, we have studied that the conventional CNN suffer from various issues such as slow learning, require huge dataset, spatially invariant to the data and gradient handling issues. Here, we measure the classification performance by using architecture depicted in Figure 6. Here, we have adopted the CNN and LSTM model to deal with the drawbacks of CNN such as gradient diminishing problem. Due to which the classification output is degraded. To demonstrate the efficacy of proposed system, we preset an ablation study here. In this study, we discard the LSTM module from the overall network architecture and measure the classification performance. Figure 7 depicts the architecture used in ablation study. The accuracy, precision, recall and F-measure outcomes are demonstrated in Table 5. The ablation study is carried out for varied rate of data training and testing as 60%-40%, 70%-30%, and 80%-20% for training and testing rates, respectively.

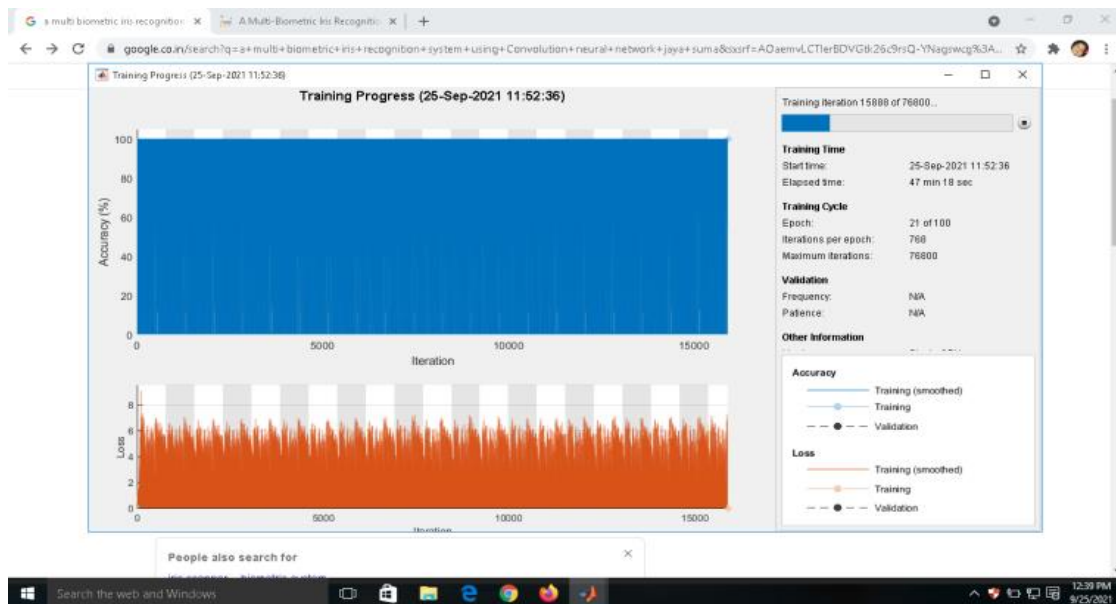


Figure 6. Training iteration 15800 of 76800

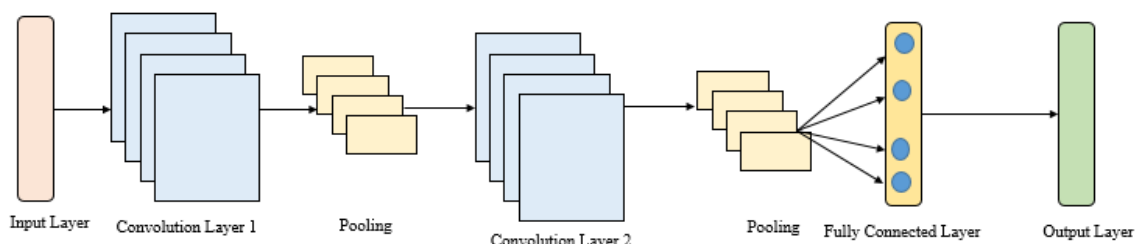


Figure 7. Ablation architecture

Table 5. Performance analysis for ablation architecture

	Accuracy	Precision	Recall	F-Measure
80-20%	97.12	97.11	96.55	95.21
70-30%	95.68	95.21	95.8	94.7
60-40%	93.65	94.35	93.25	93.55

5. CONCLUSION

Due to the severe impact of diabetes, early-stage detection of its symptoms is a challenging and highly recommended task for research community. The existing models use the knowledge of experts which is time consumption and not reliable task. Hence, machine learning based automated system for diabetes prediction have attained immense attraction from research academia. This research focuses on deep learning model and introduces a hybrid model by combining CNN and LSTM unit for classification. This BiLSTM model mitigate the drawback of gradient vanishing and improves the learning. The comparative study shows that proposed approach outperforms existing techniques such as deep learning, decision tree, ANN, and Naïve Bayes by achieving the accuracy as 99.12%.





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