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RESEARCH ARTICLE – COMMUNICATIONS ENGINEERING

Improving Diabetic Patients Monitoring System Using (NCA-CNN) Algorithm based on IoT

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Abstract

The Internet of Things (IoT) and Artificial Intelligence (AI), particularly Machine Learning (ML), have both seen significant advancements in recent years, which has resulted in significant leaps forward in the development of health monitoring systems. Patients may now be prevented, diagnosed, and monitored remotely and at home, eliminating the need to go to health and treatment centers or spend a significant amount of money doing so. This is made possible by advancements in technology. Deep learning has been the primary focus of this research as it relates to the development of a remote health monitoring system for the diagnosis of diabetes. In the system that has been suggested, improvements have been made to both the precision of the detection and the swiftness of the data processing. The Neighbourhood Component Analysis-Convolutional Neural Network (NCA-CNN) approach that we have presented involves two stages: the first stage involves picking the most important features from all of the data, and the second stage involves categorizing the chosen features. The NCA algorithm is a mathematical method that rates the characteristics based on the results of an analysis of the data and picks the most significant aspects. After that, the most salient characteristics are categorized by a deep convolutional neural network, and an accurate diagnosis of the condition is accomplished. According to the findings that were collected, the accuracy of the approach that was suggested is 97.12%.

Publisher: Middle Technical University

Keywords: Smart Health System; Internet of Things; Diabetes; Deep Learning; CNN.

1. Introduction

These days, Internet of Things (IoT) technology and its applications have grown increasingly sophisticated, which makes it feasible to link a huge number of items over the Internet in a variety of fields, including health, industrial production, home automation, and so on [1]. Several applications in the subject of smart health have been developed to improve the treatment that patients with chronic conditions get and the quality of life these patients enjoy. Because they play a very essential role in monitoring and regulating patients suffering from chronic conditions such as cardiovascular disease and diabetes [2], mobile health services are becoming increasingly important as a result of the usage of the IoT. [2] This is because mobile health services are becoming more vital. When it comes to the topic of smart health, and more especially the monitoring of patients, we have found that patient data is really helpful. To put an IoT program into action in this industry, one has to make certain that a significant quantity of data obtained via the assessment of a patient's medical symptoms is recorded. Analyses may be performed to determine whether individuals need "preventive care" to stop the progression of their ailment and identify such individuals. For instance, patients who are in the early stages of certain illnesses might be able to benefit from preventative treatment owing to big data [3]. For instance, heart failure is commonly triggered by specific risk factors, such as high blood pressure or diabetes. To preserve certain patients' lives, they must provide confidential information about themselves so that their overall health may be improved [4].

Several chronic illnesses are prevalent in today's society, including diabetes, cancer, chronic lung disease, heart disease, and stroke. Diabetes is a serious illness that has only relatively recently emerged as one of the top causes of mortality throughout the globe. Diabetic patients need to be closely and carefully monitored to preserve their health. Because insulin resistance is the root cause of diabetes and inadequate insulin production may either cause a rise in or a reduction in blood glucose levels, the primary difficulty for a diabetic patient is to keep glucose levels stable over an extended period. If they are no longer able to fulfill these requirements, some individuals need rapid medical attention to avoid a deterioration of their condition [5].

Continuous Glucose Monitoring (CGM) devices, which are a novel way of continuous monitoring and have grown more popular as a result of an increase in the number of diabetes patients throughout the globe, are being used to regulate a growing number of diabetic patients. They offer information on the current glucose levels very immediately.

Nomenclature & Symbols			
IoT	Internet of Things	CGM	Continuous Glucose Monitoring
CD	Chronic Diabetes	SMBG	Self-Monitoring Blood Glucose
ICT	Information and Communication Technology	AI	Artificial Intelligence
BG	Blood Glucose	RF	Random Forest
MLP	Multilayer Perceptron	LSTM	Long Short-Term Memory
MA	Moving Average	LR	Logistic Regression
EH-DDNN	Exploratory and Duplex Deep Neural Network	EHP	Equivalent Heuristic Pruning
DDNN	Duplex Deep Neural Network	ROC	Receiver Operating Characteristic
UCI	University of California, Irvine	KNN	K-Nearest Neighbors
PCA	Principal Component Analysis	NCA	Neural Co-occurrence Analysis
CNN	Convolutional Neural Network	KF	Kalman Filter

2. Problem Statement

One of the disorders that causes structural changes and affects the metabolic processes of the body is chronic diabetes, which is also commonly abbreviated as CD. Chronic diabetes is a condition that frequently affects people. By the end of 2014, the total number of people living with diabetes around the globe had reached 422 million. This figure represents a 100 percent rise from the previous year.

The classification of diabetes into either type 1 or type 2 sickness is a frequent practice. Additionally, there is a condition known as gestational diabetes that falls under this category. One of the top causes of mortality, diabetes type 2, is becoming more widespread in every corner of the globe with each passing year. Diabetes type 2 is one of the primary causes of death. Because their bodies are unable to produce a sufficient amount of insulin, people are at potential risk, regardless of their age or gender. It does not make a difference whether they are male or female; this is always the case. There is a connection between having a high level of blood sugar and an increased risk of mortality in humans owing to diseases such as pneumonia, stroke, and acute myocardial infarction. This is because hyperglycemia is associated with an increased risk of death. There are a variety of cardiovascular consequences that may arise as a result of inadequate monitoring of the progression of diabetes. These complications include stroke, high blood pressure, and other cardiovascular issues. When it comes to the prevention and reduction of difficulties that are brought on by diabetes, the technique that is used to monitor the amount of glucose in the blood plays a crucial role. A portable SMBG (Self-Monitoring Blood Glucose) device can serve as an efficient real-time management system to monitor the health status of diabetic patients. Innovative information and communication technology (ICT) is used in conjunction with biosensors to accomplish the functions of this gadget. The person who is receiving treatment can independently monitor the fluctuations that affect his blood glucose level. CGM devices provide users with the opportunity to have a better understanding of the changes that occur in their blood glucose levels. CGM devices get their name from the acronym for continuous glucose monitoring.

It is a strategy that is both logical and systematic, and it provides us with accurate information on diabetes patients. An approach that might be used is the monitoring of individuals with diabetes. The use of monitoring systems for diabetic patients, particularly those that make use of devices that are connected to the IoT, is a crucial component in the process of monitoring the health of the patient. Diabetes Patients are monitored using diabetic patient monitoring systems, which are meant to keep track of diabetic patients by monitoring their blood glucose levels, body temperatures, and whereabouts. The most important goal of these systems is to do this. In addition to that, it is feasible for these systems to store certain data that is connected to these parameters. In addition to being able to categorize data via the use of methods that are associated with ML, the goal of this system is not limited to only monitoring patients. As a result of the fact that it helps diabetic patients, their families, physicians, and medical researchers make decisions on the treatment of diabetic patients based on vast quantities of data, predictive analytics is a crucial tool for diabetic patients. Consequently, this is the reason why it is important for people with diabetes. A unique method for monitoring diabetic patients is presented in this work, along with an explanation of the predictive analysis accomplished via the use of a hybrid ML algorithm. The findings of this investigation are what led to the development of the system. The efficacy and accuracy of the algorithm that was used will be assessed and compared during this talk. As a result of this, the objective of this paper is to address the problem of the necessary preprocessing of diabetes-related data for higher steps, as well as to design a diabetes prediction system that is based on ML methods and has an appropriate level of accuracy. This system is intended to be implemented on the platform of the IoT and can make the appropriate decisions regarding the patient remotely. Putting it another way, the purpose of this study is to address the problem of the required preprocessing that must be performed on data connected to diabetes to proceed to higher phases. And last, but certainly not least, a comparison of the effectiveness of the methodology that was recommended with that of other ways

3. Related Works

Several papers addressed monitoring system design. The authors developed an intelligent architecture for diabetes monitoring that uses smartphone sensors to track diabetic patients' health [6]. Another study used Hadoop MapReduce and analytic techniques to identify diabetes types. This study predicted complications and treatment types [7]. The authors also presented a Hadoop/MapReduce diabetes prediction system in [8]. Using a Kalman Filter (KF) to decrease noise, the GlucoSim software analyzes continuous glucose monitoring data to estimate glucose concentration [9]. Many scholars have used data mining to create analysis and prediction models. In [10], Naive Bayes and Decision Tree algorithms were used to uncover diabetic dataset trends using Weka. Also, they were used in a classification model to uncover hidden patterns in a diabetic dataset [11]. Another study [12] predicted diabetes using the C4.5 decision tree method, neural network algorithm, K-means clustering algorithm, and visualization. XGBoost, Random Forest, Support Vector Machine, Neural Network, and Decision Tree are used in the ensemble modeling approach of the group-based framework eDiaPredict [13] to predict diabetes status in patients. Accuracy, sensitivity, specificity, Gini index, precision, area under the curve, area under the convex hull, minimal error rate, and minimum weighting factor were used to evaluate eDiaPredict. With 95% accuracy on the Indian PIMA diabetes dataset, our technique proved useful. Also provided is a potential IoT-based diabetes monitoring device for healthy and impaired people to monitor blood glucose levels (BG). Diabetes was classified using Random Forest (RF), Multilayer Perceptron (MLP), and Logistic Regression. LSTM, MA, and LR were used for predictive analysis in [14]. The benchmark Indian PIMA diabetes dataset was empirically evaluated. MLP beat other classifiers with 86.08% accuracy, while LSTM enhanced prediction with 87.26%. A comparison of the suggested strategy to state-of-the-art methods showed its compatibility with several public healthcare applications.

A genetic algorithm-based group training technique was used to accurately diagnose and predict diabetic complications [15]. We used empirical data from Indian diabetes patients on the University of California website. ICT advances like the IoT, ML, and data mining have made illness outcomes in daily life and healthcare predictable. This helps create better health plans to reduce illness progression and consequences. This research showed that the suggested technique could diagnose the condition with 98.8% and 99% accuracy.

IoT, big data, and AI are interconnected and affect the design and development of personalized healthcare systems. This study [16] reviews AI in IoT and medical systems and examines its use in healthcare. The literature study shows that AI is widely used in heart disease diagnostics, prediction approaches, robotic surgery, and personalized treatment. The study shows that k-nearest neighbor, support vector machine, support vector regression, Naive Bayes, linear regression, regression tree, classification tree, and random forest are the leading AI approaches. These strategies mostly analyze patient data to improve healthcare. Automatic endoscopic systems for appropriate positioning and transoral robotic surgery enable less intrusive treatments, less blood loss, and quicker recovery. IoT also aids in diabetes control, biophysical parameter monitoring, and medical decision assistance.

The Exploratory and Duplex Deep Neural Network (EH-DDNN) is suggested for early diabetes prediction [17]. We start with the Equivalent Heuristic Pruning (EHP) approach for feature selection utilizing a large dataset. EHP splits the input matrix into rows and columns. EHP optimizes subsection neighborhood assessments using conditional non-collinearity and heuristics to reduce computation time and overhead costs and eliminate unnecessary and duplicate features. A dataset with fewer characteristics simplifies early prediction. Next, a Duplex Deep Neural Network (DDNN) is developed to anticipate early utilization of the specified characteristics. To accommodate large data volumes, the DDNN uses nonlinear processing and linear response properties. Experimental validation uses benchmark datasets like the UCI repository and the Pima Indian diabetes dataset. The research compares diabetes prediction overhead, time, and ROC curves.

4. Proposed Method

In this section, our proposed method based on ML will be explained to identify people with diabetes. A diabetes detection and control system using the IoT consists of several parts, which are: 1) data collection; 2) data analysis; and 3) sending decisions after data analysis on the cloud computing platform. and the IoT. In this system, the most important part is the data analysis part, because if the data is not analyzed well, then the right decision will not be made and the whole system will face a serious problem. As a result, it is vital to provide a method based on artificial intelligence and ML for proper data analysis and, high-accuracy decision-making.

In this work, we have used a deep learning method along with a mathematical method for the optimal selection of features for the classification of diabetes data. In the rest of this section, the proposed method is explained. The diagram of the proposed method is shown in Fig. 1.

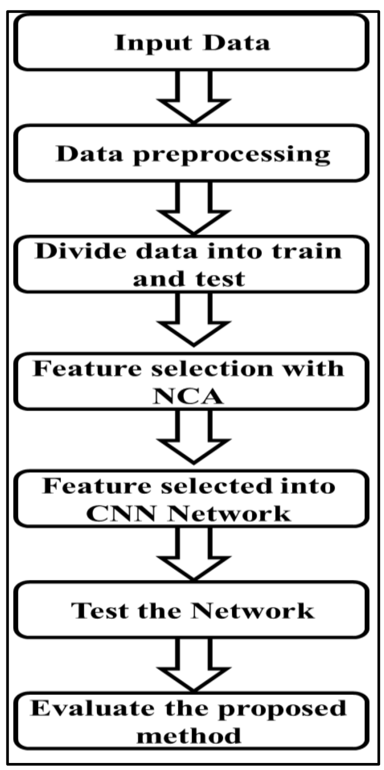

Fig. 1. Diagram of the proposed method

4.1. Dataset and preprocessing

We utilized the Pima database [18], which is associated with patient records from a hospital in the United States. This database comprises a total of 768 samples, encompassing 9 columns. The initial 8 columns contain patient characteristics, while the last column serves as the label, representing the disease diagnosis. For detailed information regarding the feature specifications, please refer to Table 1.

Table 1. Indian diabetes database profile

Property	Description	Unit
1	Number of Pregnancies	-
2	Plasma Glucose Concentration in 2-Hour OGTT	Mg/dl
3	Diastolic Blood Pressure	mmHg
4	Arm Skinfold Thickness	mm
5	Two-Hour Serum Insulin	mu U/ml
6	Body Mass Index (BMI)	Kg/m^2
7	Hereditary Function of Diabetes	-
8	Age	Years
9	Result	-

With this approach, the input data is converted in such a way that it falls within the range of [-1, +1]. The conversion formula is as follows:

$$X_n = 2\frac{X_i - X_{min}}{X_{max} - X_{min}} - 1,\ i = 1,2,\dots,N \tag{1}$$

X_{max} is the maximum value, X_n normal value, X_{min} Minimum value, and $X_i$the actual amount of network input

Modeling is done after determining the scenario and setting the input. It should be noted that in this work, 80% of the data was used for training and 20% of the data was used for testing.

4.2. Feature Selection with Neighbourhood Components Analysis (NCA)

There is a method for decreasing the number of dimensions that are used in ML and feature selection. Finding a linear transformation of the data that maximizes the ratio of between-class scatter to within-class scatter is the goal of this technique. In layman's words, it endeavors to project data points into a lower-dimensional space, one in which data points belonging to the same class are clustered together while data points belonging to other classes are spaced farther away. The categorization process is a common use of this method. The main goal of Neural Co-Occurrence Analysis (NCA) is to learn a linear transformation of the feature space that makes a later classification algorithm work better.Examples of such algorithms are K-nearest neighbors (KNN) and linear classifiers. NCA operates by taking into account the pairwise affinities that exist between the data items. It looks for a linear transformation of the feature space that will make data points that are already similar (those that belong to the same class) even more similar, while data points that are already dissimilar (those that belong to separate classes) will become less similar. formulates this as an optimization problem, the purpose of which is to maximize a certain objective function that quantifies the classification performance based on these pairwise affinities. This may be done by maximizing the value of the objective function. During the process of optimization, the transformation matrix is tweaked to locate the optimal linear transformation [19].

In the discussion of supervised learning, a series of features along with their label (desired class) are entered into the selected network, and the network in the training phase tries to find a valid mathematical pattern between the features and their label. Now, the more features there are, the harder it is to find a suitable pattern in a short time. And sometimes some features not only do not help to find a better pattern, but on the contrary, they make this task more difficult.

In this work, we use the NCA algorithm to find the weights of the features of the input data and remove those features that have zero weight. This work increases the accuracy of identification and also reduces the time of network training.

4.3. Classification with Convolutional Neural Network (CNN)

A deep Convolutional Neural Network (CNN) with outstanding pattern recognition was used to categorise the specified characteristics. The layout and number of layers of a CNN network may be customised. The layers usually are [20]:

- The Input Layer comprises raw input data.
- The Convolutional Layer: Neurons execute element-wise multiplications between their input area and weights to determine their values.
- The Rectified Linear Unit (ReLU) Layer applies a fixed function (max (0, x)) to each neuron's output, where 'x' represents the neuron's output.
- The Pooling Layer reduces dimensionality via subsampling, lowering the amount of input dimensions.
- The Fully Connected (FC) layer computes neural network output in either regression or classification mode. In the last layer, this network classifies raw data into category scores.

The convolutional network's strength is in identifying characteristics across layers. The neural network needs many parameters and training data to correctly represent information. CNN learning uses feedback. To reduce mistakes and update weights, network error is transferred from the last layer to the beginning layer. Fig. 2 shows this work's CNN network layer structure.

4.4. Internet of Things (IoT)

In the realm of medicine, the IoT plays an essential role in enhancing patient adherence to drug regimens. It is a widespread issue that results in inferior health outcomes and higher expenses associated with medical treatment when medication is not taken as prescribed. There is a possibility that IoT solutions for medication adherence can considerably improve patient outcomes, minimize hospital readmissions, and cut overall healthcare expenditures. They give people the ability to take charge of their health and supply medical professionals with vital data that can be used to deliver more individualized treatment. When using these technologies, it is vital, however, to address issues around patient privacy and data security to secure patient data and maintain compliance with applicable healthcare standards [21].

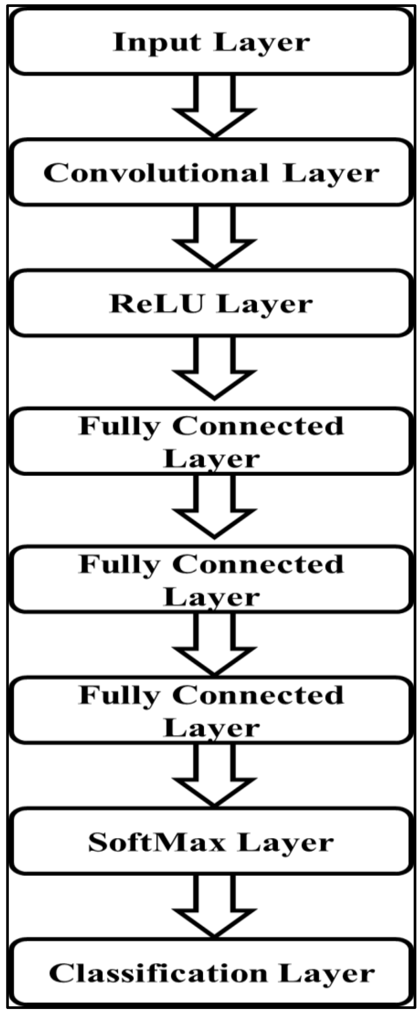

Fig. 2. CNN layer arrangement for the proposed model in this paper

5. Result and Discussion

In this section, we evaluate the proposed method. In this section, we have simulated two scenarios. The first scenario is without feature selection using the NCA method, and the second scenario uses the NCA method to select the optimal features. Finally, the accuracy obtained for identifying diabetic patients has been compared with the other methods. It should be mentioned that all the simulations in this paper have been done using MATLAB software version 2021.

5.1. Evaluation criteria

The following equation that calculates the accuracy of the proposed method is used to check the accuracy of the classification efficiency:

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

Where *TP*: True Positive, *TN*: True Negative, *FP*: False Positive, and *FN*: False Negative.

5.2. First mode: classification without NCA algorithm

In this case, all the features are directly entered into the CNN network for classification after the pre-processing stage and data division. Next, the training and error results in the proposed CNN network with 8 different layers are shown in Fig. 3, and Fig. 4 shows the characteristics of network training.

According to Fig. 4, the time required to train the network in this case is 12 seconds for 150 epochs. Fig. 5 shows the confusion matrix for this situation.

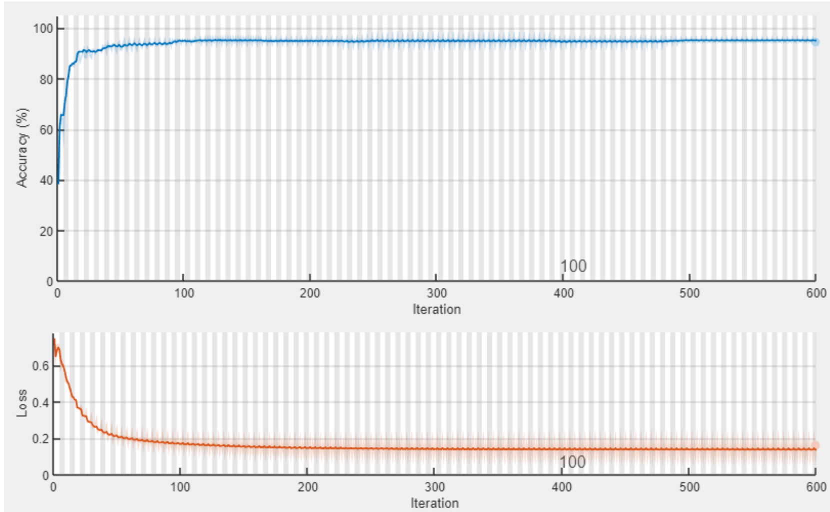

Fig. 3. Training and error graph in the proposed CNN network without considering NCA

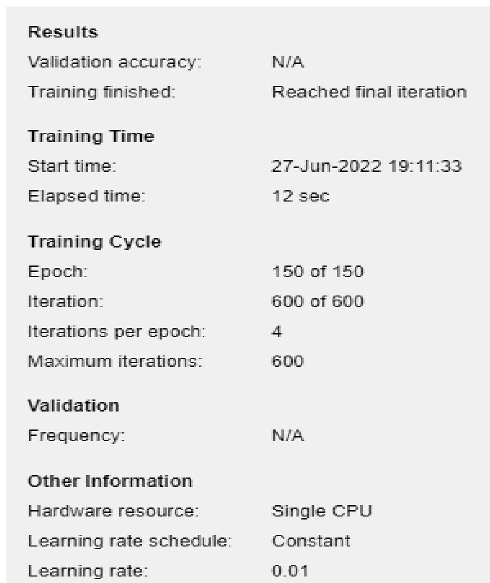

Fig. 4. Training profile of the proposed CNN network without considering NCA

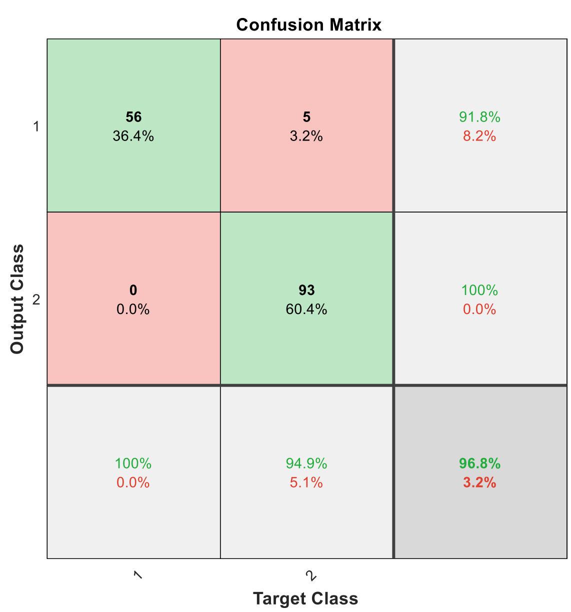

Fig. 5. Confusion matrix without NCA algorithm

As seen in Fig. 5, the overall accuracy for the proposed CNN network has reached 96.8%.

Of course, this figure is only the result of running the program once, and for an accurate comparison, the average should be taken from dozens of running the program.

5.3. The second mode: using the NCA algorithm

In this case, we use the NCA algorithm to select the optimal features. As can be seen in Fig. 6, out of 8 features related to this database, the first, fourth, and sixth features have less weight than other features. As a result, we used only features 2, 3, 5, 7, and 8 for evaluation, and these features are entered into the proposed CNN network.

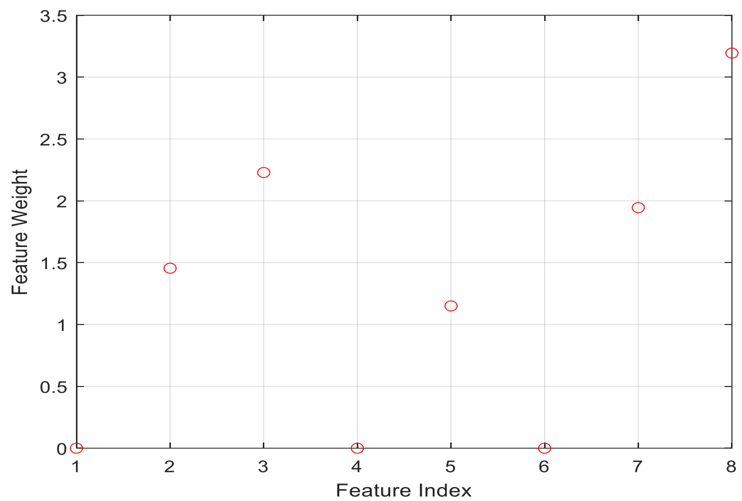

Fig. 6. Weighting of features using the NCA algorithm

Figs. 7 and 8 show the training and error diagrams as well as the general characteristics of the proposed network considering the NCA algorithm. Meanwhile, the training time in this mode is 11 seconds, which is 1 second less than the mode without NCA.

In Fig. 9, the confusion matrix is drawn for the classification of two classes of diabetes and healthy disease in the case of the proposed method (with the NCA algorithm). As it turns out, the overall accuracy for one run is 98.1%.

In the next section, the average accuracies compared to the methods of the reference article are given.

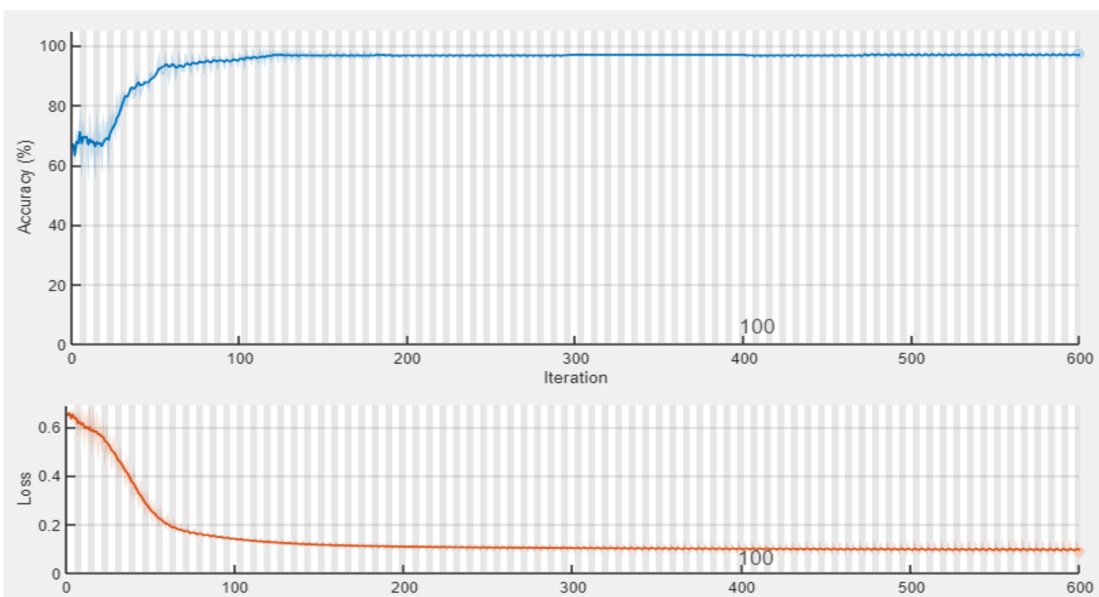

Fig. 7. Training and error graph for the proposed CNN considering NCA

Fig. 8. General characteristics diagram of the proposed CNN network considering NCA

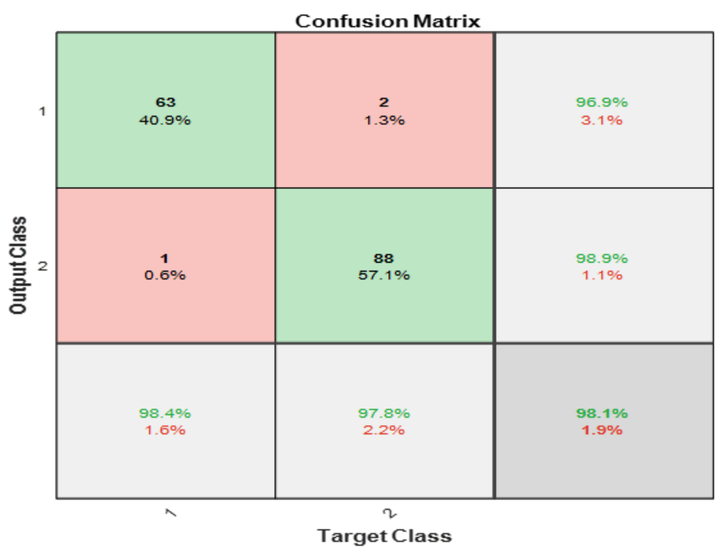

Fig. 9. Confusion matrix with NCA algorithm

5.4. Comparing results

Table 2 shows a comparison of the accuracy of identifying diabetes by the methods of the reference article as well as our proposed method in two cases. The accuracy mentioned in this table for the proposed method is the result of the average of 50 independent executions of the simulation program.

Table 2. Classification results of different methods on the Pima diabetes database

Method	Accuracy
Naïve Bayes [22]	85.11
Random Forest [22]	96.05
OneR [22]	70.40
SMO [22]	89.62
Proposed method (CNN)	96.38
Proposed method (NCA-CNN)	97.12

According to Table 2, the proposed method with the NCA algorithm is preferable to other works in terms of disease identification accuracy.

6. Conclusion

In this study, the diagnosis of diabetes using deep learning and a remote medical monitoring system is the primary focus of our efforts. The speed at which a disease may be diagnosed and its accuracy are both very significant components of a medical monitoring system. The NCA-CNN approach, which has a high ability to detect with fast speed and accuracy, was suggested by us in this study. The NCA algorithm is used to find the best and most effective features, and then the CNN deep network classifies these ideal features. In the suggested technique, employing all of the characteristics of the gathered data would incur a huge computational cost. Instead, the method finds the best and most effective features first, and then classes these optimal features. The result is an improvement in both the accuracy and the speed of the data analysis.

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