

## Exploiting Machine Learning Algorithms to Diagnose Foot Ulcers in Diabetic Patients

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### Abstract

**INTRODUCTION:** Diabetic foot ulcer (DFU) is a complication of diabetes that affects most of the diabetic patients. It will cause open wounds on the foot. Untreated DFU will lead to amputation and infection, which results in removal of foot or leg. As diabetes is the major health problem faced by people of all age groups, identifying foot ulcers at an early stage is essential. In this context, an efficient model to predict the foot ulcer accurately was proposed in this work.

**OBJECTIVES:** To predict DFU using an effective neural network algorithm on a suitable dataset that consists of risk factors and clinical outcomes of the disease.

**METHODS:** In recent days, ML techniques are most commonly used for predicting various diseases. To achieve the objectives a neural network technique, namely extreme learning machine (ELM) is proposed to predict DFU accurately. In addition, three existing algorithms, namely KNN, SVM with Gaussian kernel and ANN are also considered. These are implemented in R programming.

**RESULTS:** Algorithms compared in terms of five evaluation metrics accuracy, zero-one loss, threat score/critical success index (TS/CSI), false omission rate (FOR) and false discovery rate (FDR). The values of accuracy, 0-1 loss, TS/CSI, FOR and FDR obtained for ELM are 96.15%, 0.0385, 0.95, 0 and 0.05 respectively.

**CONCLUSION:** After comparison, it was discovered that ELM had outperformed other algorithms in terms of all the metrics. Thus, it was recommended to use ELM over other algorithms while predicting diabetic foot ulcers.

**Keywords:** Diabetic foot ulcer, KNN, SVM with Gaussian kernel, artificial neural network (ANN), extreme learning machine (ELM), accuracy, zero-one loss, critical success index (CSI), false omission rate (FOR) and false discovery rate (FDR).

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### 1. Introduction

Diabetes leads to several complications where foot ulcers are one of them. This disease occurs in type-1 and type-2 diabetic patients. In type-1 diabetic patients, there will be no insulin production or produced in less quantity, so that the patient should depend on insulin injections. In type-2 diabetic patients, insulin will be produced, but it was not sufficient for

the body's functioning. In type-2, the diabetic patient is given medication instead of insulin injections [1].

Long term suffering of either type-1 or type-2 diabetes increases the risk of affecting diabetic foot ulcers. A Diabetic foot ulcer is a condition where the diabetic patient will suffer from a wounded foot. It mostly occurs on the bottom of the foot and stays open. Nearly 15% of diabetic patients will be affected by foot ulcers. Among those people, about 6% are hospitalized because of further complications. On average,

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patients having diabetes for more than 10 years are affected with DFU [2].

A diabetic patient should observe the foot ulcer changes to identify foot ulcers in an early stage. Few symptoms like swelling, redness, cracks, pus, sores, odor from any foot, gangrene, and open lesions are very helpful to identify in the initial stage. These symptoms may vary from person to person. Most of the patients will suffer from drainage from the foot, which is the first sign. Untreated foot ulcers may lead to complications like infection, amputation, hospitalization, and death. If the infection gets serious without proper treatment, it may lead to loss of limb or gangrene. Gangrene is a condition that causes the death of tissue due to infections [3]. Amputation is a non-healing ulcer that leads to removing the foot or any part of the leg because of severe tissue and bone damage. Feet of a diabetic foot ulcer patient is provided in figure 1.



**Figure 1.** Diabetic foot ulcer

This disease is most common in diabetic patients who are suffering from nerve damage (neuropathy). The ball of the foot and the big toe bottom are the most common chances of ulcers occurring. Smoking is also one of the significant reasons for affecting foot ulcers. Chain-smoking will affect small blood vessels. This will decrease blood flow to the feet, and the healing process may slow down. The risk factors of foot ulcers are poor hygiene, alcohol consumption, retinopathy, neuropathy, nephropathy, cardiovascular, obesity, smoking habit, and peripheral vascular disease. If diabetic patients have any risk factors, the chance of affecting diabetic foot ulcers will increase [4].

From an observational study [5] conducted on the severity of DFU, illiterate patients and lower socioeconomic status are identified with an increase in the severity of DFU. It was due to the habit of walking barefoot. By taking proper foot care and using footwear, the chances of increasing severity will be reduced.

In a study of diabetic foot ulcers, more than 70% of the diabetic patients diagnosed with foot ulcers had observed the increase in disease severity in successive 5 years [6]. Some preventive measures can reduce the severity of the disease, like controlling sugar levels in the blood and blood pressure,

maintaining proper skin and nail care, using good footwear outdoors and indoors, and avoiding smoking. Maintaining normal sugar levels and blood pressure will improve the healing power and help speed recovery [7].

Good health service is mandatory for a developing country to overcome the limitations in resource availability, health care professionals, and government expenditures. Technology driven services play a vital role to minimize the efforts and expenditure for the government. Internet of things (IoT) and cloud computing are two leading technologies in the healthcare sector [8]. IoT has changed the tradition of consulting a medical expert either by visiting a hospital or through telecommunication. It's been called as Internet of Medical Things (IoMT) for its stellar role in the healthcare sector. IoT devices to monitor glucose levels, blood pressure, and heart rate, etc. are used mostly to monitor health conditions. As a result, complexity of storing and analysing the electronic medical records, i.e. data collected from IoT devices increases. Cloud computing can make it easier by storing vast data on a virtual cloud [9]. High data storage at low cost, backup maintenance, and secured data storage are its major advantages.

In healthcare sector image processing and machine learning is being used wisely, where the dataset is the primary requirement for predictive analysis of a disease. Image processing, enhances the images captured by various means and analyses those enhanced images to make a decision. It's widely used in different fields like medical, robot vision, and face detection. In the healthcare sector, image enhancement plays a vital role. For example, analysis performed on enhanced images of several medical imaging techniques like CT scan, UV imaging, and X-Ray, etc. helps to predict the disease efficiently [10]. However, machine learning which includes neural network techniques for analysing and detecting various problems and strengthens the decision. Most of the ML algorithms use feature vector to analyse the data. It can detect nonlinear relationships between predictor and target variables efficiently. Also can predict output from the unforeseen input data based on the available feature data. However, image processing can't predict accurate output for unforeseen input.

Early diagnosis and treatment of diabetic foot ulcers will reduce the risk of affecting its further complications. As discussed above, machine learning is widely used in the healthcare sector, helping the doctor or the physician provide care in the initial stage. This can reduce costs and give better results, as proper care will be provided in the early stage [11]. So, in this context, some machine learning algorithms are chosen to predict diabetic foot ulcers better.

The techniques, namely K- nearest neighbor, SVM with Gaussian kernel, and artificial neural network, are the existing algorithms chosen. Comparison between existing algorithms and the proposed algorithm, i.e., extreme learning machine (ELM) shed light on the results. The implementation used the R programming language. Evaluation metrics like accuracy, zero-one loss, threat score/critical success index, false omission rate, and false discovery rate are considered for evaluating and comparing algorithms. In addition to these metrics, cross-entropy error or log loss is also used to

compare the neural network techniques. In the considered algorithms, there are two neural network techniques ANN and ELM. So, these two techniques are compared based on log loss value. Finally, identifying the best performing algorithm based on five evaluation metrics and log loss is used to determine the best neural network.

## 2. Literature survey

Reddy et al. [12] used a voting strategy for the detection of diabetes. Pima Indian diabetes dataset is taken from the UCI ML repository. Data mining techniques like decision tree, naive Bayes, SMO, SVM, and AdaBoost-M1 are implemented using the k-fold cross-validation technique in their work. The best algorithm among the four will be identified for an overall accuracy of 95% using a voting strategy.

Ahmed [13] developed a model to classify diabetes depending on the previous medical records. This work considered real-world data from the Health facts database. The developed model will predict if the patient has diabetes or not, based on the HbA1C value (level is in control or out of control). Naive Bayes, logistic regression, and J48 are the data mining techniques selected to develop the predictive model. After comparison, logistic regression (LR) had the best performance with good values for overall accuracy, f-measure, precision and recall as 74.4%, 0.653, 0.73 and 0.744.

Reddy et al. [14] highlighted their work on using deep learning technique to predict diabetes patient hospital readmission. The considered dataset consists of 47 features and 1,01,766 instances. Deep belief network is the deep learning technique proposed in their work. It was compared with five other ML techniques like the random forest, logistic regression, AdaBoost, gradient boosting, and decision tree. For evaluation and comparison of algorithms, metrics like accuracy, specificity, precision, f1-score, and NPV are chosen. Among all algorithms, LR obtained a 0.7833-f1 score and DBF was the best algorithm with accuracy of 0.6917, precision of 0.6814, specificity equal to 0.6644, and NPV of 0.7032.

Sneha and Gangil [15] performed an early prediction of diabetes. The dataset is taken from the UCI machine learning repository. A feature selection technique is performed based on correlated values of the attributes in the dataset. Algorithms like KNN, SVM, naive Bayes, random forest, and decision tree are then implemented on the optimal features in their work. The naive Bayes algorithm has performed better with 82.3% accuracy.

Reddy et al. [16] performed a review study on predicting diabetes and its correlated ailments using data mining techniques. Based on different studies presented by various authors, some methods, such as I-SVM, fuzzy, C4.5, neurocognitive, and image Net, are compared with each other. Among all these techniques, image Net has achieved the highest accuracy while using the k-fold cross-validation technique.

Kasbekar et al. [17] developed a tool for identifying the risk of diabetic foot amputation. Single C5.0 and boosted C5.0 boosted algorithms are implemented on the diabetic foot patient dataset. After comparing these techniques, boosted C5.0 was better with 96% accuracy on test data. It has misclassified only two instances in the dataset, which indicates the least failure percentage.

Reddy et al. [18] proposed their work for predicting the occurrence of a single or combination of ailments correlated to diabetes. Mainly the ailments, viz. kidney malfunction, retinal disorder, and heart disease, are considered. The dataset was the Regional Diabetes-related Ailment Dataset (RDAD) from the medical center in Vijayawada. Fuzzy logic is the technique proposed, which employed k-fold cross-validation. The proposed model is compared with other schemes, and it was observed that the proposed model had achieved a better value of overall accuracy 97% and 80 ms time for computation.

Pushpaleela et al. [19] considered SVM, naive Bayes, KNN, C4.5, and decision tree classification techniques to predict DFU in type-2 diabetic patients. The dataset used is a real-world dataset collected from a hospital. It contains the data related to 455 persons, 355 are diabetic patients, and 100 are non diabetic patients. After implementing all techniques, they are compared based on obtained accuracy. SVM has performed better than the remaining algorithms with 92.22% of accuracy.

Reddy et al. [20] analyzed various ML techniques in the context of predicting diabetes. Gradient boosting, logistic regression, adaptive boosting, random forest, and decision tree techniques are performed on the diabetes hospital readmission dataset. Accuracy and f-measure with values of 0.665 and 0.783 are obtained for gradient boosting, which is the best one.

Sudarvizhi et al. [21] identified and analyzed foot ulcers using a technique called a load cell. The sensors named load cell are inserted in the foot mat. SVM was implemented on the data obtained from sensors and has achieved nearly 94.6% accuracy and 95.2% precision.

Adam et al. [22] detected DFU in patients with and without neuropathy. Decision tree, probabilistic neural network, SVM with Gaussian kernel, KNN, LDA, and QDA techniques were implemented on the hospital dataset related to DFU in patients with neuropathy as well as without neuropathy. KNN with locality sensitive discriminant analysis feature reduction has obtained 93.16%, 90.91%, and 98.04% of accuracy, sensitivity, and specificity, respectively. It was observed as the best algorithm among all.

Goyal et al. [23] proposed a computer vision technique to diagnose ischaemia and infection separately in the patients of DFU. The ensemble Convolution Neural Networks (CNN) with super pixel color descriptor is used for diagnosis using an image dataset. This technique performed better with 90% accuracy for ischaemia and 73% accuracy for infection. Wang et al. [24] determined the area of DFU by using cascaded 2-stage SVM-based classification. Traditional ML techniques were also compared with this proposed technique. After evaluating cascaded 2-stage SVM, 73.3%

sensitivity and 94.6% specificity were obtained, indicating better performance than benchmark SVM and ANN.

Botros et al. [25] presented their study on the prediction of diabetic foot ulcers. This was done based on dynamic pressure distribution. The dataset selected contains dynamic plantar pressure measurements for 28 non diabetes and 56 diabetes patients without diabetic neuropathy. DFU is predicted separately in these three cases of the dataset. SVM is the ML technique selected for their work. Firstly, the plantar surface is divided into 11 regions. Then, preprocessing is performed, followed by feature extraction and selection. Then, SVM is implemented, which has obtained precision, ROC, and accuracy of more than 95.2%, 0.946, and 94.6%, respectively, in all the three cases of the considered dataset.

Patel et al. [26] focused on medical image processing to detect and classify the DFU wound. The four steps involved in the foot ulcer detection system are image preprocessing, image segmentation, feature extraction, texture detection and image classification. The classification techniques used in their work are KNN, SVM, fuzzy logic, Bayesian networks, and neural networks. Then, the DFU wound is classified into three groups slough, necrotic, and granulation. The algorithms' evaluation was not done based on metrics. Comparison of the algorithms to identify the best one was also not performed. Instead, the cluster of images for these three groups is obtained.

Keerthika et al. [27] highlighted their work on predicting DFU. This investigation considered the image dataset obtained by consulting doctors. The prediction happens based on image segmentation. This was done using the watershed and region growth algorithm. These algorithms are used to obtain the accurate wounded area from the images. Then, the single-stage SVM algorithm performs classification. The output result will be obtained as different stages of the wounded image, specifically the initial and final stages.

Cui et al. [28] presented their work on diabetic wound segmentation based on CNN. The diabetic foot ulcer image dataset provided by New York University was considered. Initially, preprocessing was performed followed by image segmentation using patch-based CNN and post-processing. The post-processing includes the output from the CNN, a probability map that gives the final result of wound segmentation. The comparison of their proposed work and other segmentation methods, namely SVM and U-net, is done. From the comparative analysis, the proposed technique obtained better values than SVM with values of precision, sensitivity, specificity, pixel accuracy, mean IoU, dice, and MCC as 0.722, 0.9, 0.947, 0.934, 0.660, 0.770, and 0.753, respectively.

Veredas et al. [29] focused on the identification of tissues in images of wounds. For this, a hybrid approach based on Bayesian network and neural network is proposed. The region segmentation was performed using mean shift and region growing techniques, through which the features of color and texture of wounds are obtained. The k-fold cross-validation technique is used in this work. Bayesian Committee Machine (BCM), which combines the neural

network output, and Ensemble-Averaging Committee Machines (EACM) are used for classification. Some heuristics were also considered to improve the classification results. Finally, after obtaining results, BCM and EACM are compared with similar ML classification techniques like SVM and multiclass Bayesian Committee Machine. After comparison, it was found that EACM with heuristic has performed better with an overall 85.7228% of sensitivity, 96.4307% of specificity, 91.0767% of success and 94.2891% of accuracy.

Sudha et al. [30] classified the risk of diabetic foot ulcers into different levels of disease severity. The dataset is collected from the Karnataka Institute of Endocrinology and Research (KIER). Decision tree algorithms CART and random forest are implemented using feature selection evolutionary techniques, namely particle swarm optimization (PSO), bat algorithm (BA), genetic algorithm (GA), gravitational search algorithm (GSA), cuckoo search (CS), fire fly (FF) and dragonfly (DF). After obtaining results, the comparison is made in terms of accuracy. The CART algorithm with firefly feature selection obtained good accuracy of 79.73%. The overall accuracy of the model is 77%.

The next section, i.e., section 3 demonstrates the work methodology that describes the dataset used and the architecture of the proposed work. Section 4 demonstrates the four algorithms used in this work, the proposed techniques ELM was elaborated, and the remaining algorithms are explained briefly. Section 5 has Metrics used and Section 6 will provide the complete details and information about the obtained results and discussion. Section 7 will provide the future work. Lastly, section 8 is the conclusion is provided after generalizing all the previous works and this work.

### 3. Research approach

This section comprises details regarding the work's objectives, a description of the chosen dataset, and the methodology.

#### 3.1. Objectives of work

Identification of any disease in an early stage will help to take the treatment immediately. Accordingly, treatment in time of any illness will reduce the chance of further complications and support speed recovery. As diabetic foot ulcer is the major side effect of diabetic patients, its early detection is vital to avoid future complications. So, this problem was considered in this work, and the main objectives are as follows

- Choose an adequate dataset and develop a useful predictive model for a diabetic foot ulcer.
- Predict diabetic foot ulcer disease more accurately than existing related works.
- Identify the best performing algorithm among all the considered algorithms.

In this work, the selected dataset contains various risk factors and clinical outcomes of diabetic foot ulcers. So, an effective model could be developed, and an accurate result will be obtained. In this context, few existing algorithms are chosen along with one proposed algorithm. KNN, SVM with Gaussian kernel, and ANN are the existing algorithms, and ELM is the proposed technique. To obtain an effective model, the best performing algorithm was identified and suggested to use in further works. So, 5 evaluation metrics were considered, based on which the best algorithm was identified. These metrics are accuracy, 0-1 loss, TS/CSI, FOR, and FDR. This entire process was done in R programming. The details about the dataset and the methodology are provided in the following subsections.

### 3.2. Dataset

Dataset selected in this work is consists of 22 attributes and 133 instances. It was taken from the "Figshare" data repository. In this dataset, 21 attributes are the predictor or independent features, and 1 attribute is the target or the dependent feature. The attributes from 1 to 21 in table 1 are the predictor attributes. The 22nd attribute, named as Ft\_ulcer, is the target attribute that classifies the dataset into two categories, tested positive and negative for diabetic foot ulcers, respectively. Accordingly, it is called a binary classification problem. In the dataset, attributes, i.e., neuropathy, nephropathy, retinopathy, PVD, and CDV, are the diabetic complication diseases. Neuropathy is a nerve disease, nephropathy is a kidney disease, and retinopathy is an eye disease. Peripheral vascular disease (PVD) is the disease of poor blood circulation that mostly affects blood vessels' functioning in the brain and outside the heart. CDV is a cardiovascular disease like heart stroke. Ft\_ulcer is the considered disease foot ulcer.

7.	FBS	Fasting Blood Sugar levels. Its normal range is 70-110 mg/dL.
8.	HbA1C	Average blood sugar levels for past two to three months.
9.	LDL	Low-density cholesterol (bad cholesterol). Its normal range is <100 mg/dL for both men and women.
10.	HDL	High-density cholesterol (good cholesterol). Its normal range is $\geq 40$ mg/dL and $\geq 50$ mg/dL for men and women respectively.
11.	TG	Triglyceride. Its normal range is less than 150 mg/dL.
12.	Statin	Statin drug usage to control cholesterol. 1-Ator, 2-Ros and 3-No statin.
13.	Dose	Dose of statin the patient was suggested taking 0, 20, 40, 80. 0 means no statin usage and remaining values indicate mg of statin suggested to use.
14.	Sys_BP	Systolic blood pressure. Its normal range is $\leq 120$ mmHg.
15.	Dias_BP	Diastolic blood pressure. Its normal range is $\leq 80$ mmHg.
16.	Neuropathy	Tested 0-negative or 1-positive for neuropathy.
17.	Nephropathy	Tested 0-negative or 1-positive for nephropathy.
18.	Retinopathy	Tested 0-negative or 1-positive for retinopathy.
19.	PVD	Tested 0-negative or 1-positive for PVD.
20.	CDV	Tested 0-negative or 1-positive for CDV.
21.	Smoking	0-no, 1-yes indicates smoking habit.
22.	Ft_ulcer	Tested 1-positive or 0-negative for diabetic foot ulcers.

Table 1. Description of the dataset

S. no.	Attribute	Description
1.	Gender	Gender of the person. 1-Male, 2-Female.
2.	Age	Age of the person in years.
3.	BMI	BMI-Body Mass Index (Height in kg/Weight in m <sup>2</sup> )
4.	DM_type	Type of diabetes the person has. 1-Type I, 2-Type II.
5.	DM_duration	Duration of the diabetes in years.
6.	DM_treat	Type of treatment given to the diabetic patient. 1-Insulin intake, 2-Oral and 3-Both oral & insulin.

The box plot for each of the predictor attribute with respect to the target attribute is demonstrated in Figure 2. A box plot is generally used to show the distribution of data. The 21 predictor attributes are represented along the x-axis and its values are represented along the y-axis. The two possible classes for the target attribute Ft\_ulcer are positive and negative, as described in table 1. In this figure the negative, and positive classes are shown using red and blue color respectively. Each box plot shows the values of minimum, maximum and inter-quartile range. The inter-quartile range represents the 25th percentile (1st quartile), median and 75th percentile (3rd quartile). This region is shown as the box. The lowest end indicates the minimum value and highest end indicates maximum value.

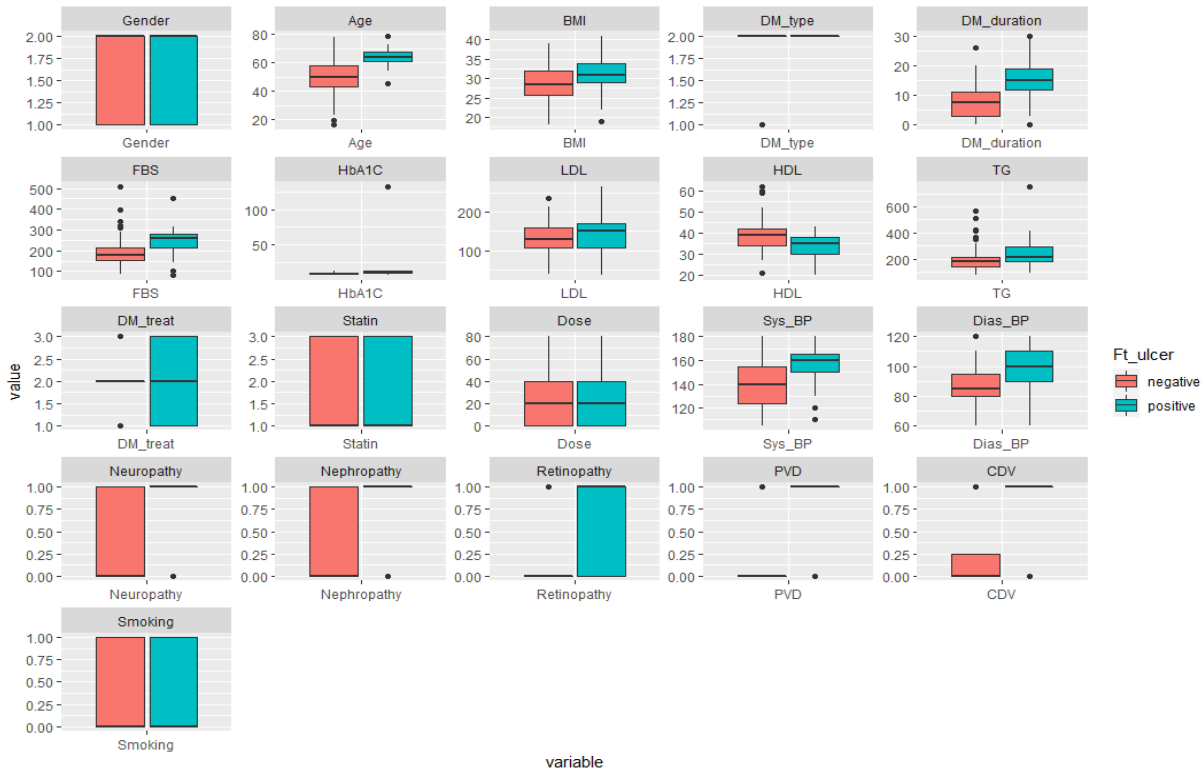


Figure 2. Box plot for the dataset attributes

### 3.3. Methodology

The methodology of the work is demonstrated in figure 3. Data pre-processing is performed on the loaded dataset. Then percentage split of 80% was used for training and 20% for testing with 107 and 26, respectively. Then three existing algorithms and one proposed algorithm are implemented in R programming individually. A training model is obtained after implementing each algorithm. These trained models are evaluated on the test dataset and get the result in terms of evaluation metrics. Accuracy, 0-1 loss, threat score/critical success index, false omission rate, and false discovery rate are the performance metrics considered in this work. All four algorithms are compared based on evaluation metrics to identify the best one among all. In this work, the proposed algorithm ELM has obtained better values than the remaining algorithms.

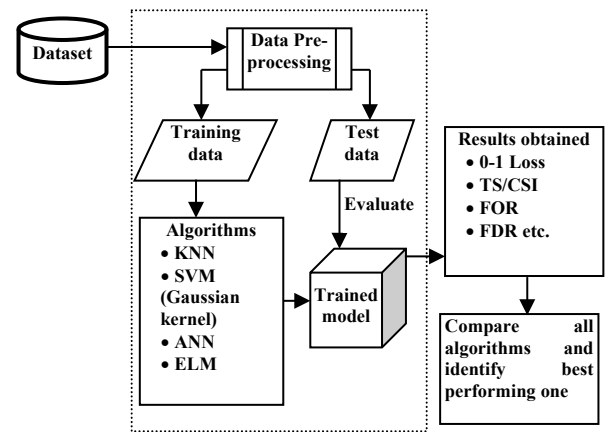


Figure 3. Methodology

### 4. Algorithms used

The algorithms used in this work are explained in this section. KNN, SVM with Gaussian kernel, and artificial neural network (ANN) are the considered existing algorithms. To these techniques, a brief introduction and details are provided. Extreme learning machine (ELM) which is the proposed technique, is explained in a detailed manner.

#### 4.1. KNN

K-Nearest Neighbor(KNN) is an ML classification technique. By calculating the Euclidean distance as given in formula (5), the prediction was made. In this technique, the Euclidean distance between each test data point and all data points in the training dataset was obtained. Then they are arranged in ascending order, according to the Euclidean distance values. The most frequent value from the top K rows is given as the predicted value. In formula(5) t indicates each predictor

attribute,  $n$  is the total number of predictor attributes,  $x_t$  and  $y_t$  indicate data point in the training dataset and test dataset for attribute  $t$ , correspondingly [31]. In this work, after implementation, the optimal value of  $K$  chosen is 9.

$$D(x, y) = \sqrt{\sum_{t=1}^n (x_t - y_t)^2} \quad (5)$$

## 4.2. SVM with Gaussian kernel

Support Vector Machine (SVM) has different types of kernel methods which can be used for classification purpose. Gaussian kernel or radial basis function (RBF) kernel is one of those techniques. In this technique, the conversion of feature space was performed by using the formula (6). The feature space with low dimension was converted to high dimension in order to obtain better results when the data is not linearly separable. Then hyperplane is constructed in the high dimensional feature space. The hyperplane with maximum margin was selected among all the possible hyperplanes. This hyperplane separates the data into two categories, namely positive and negative, in the case of disease prediction, based on which the prediction was made. The formula (6) is the Gaussian function where  $\sigma$  is a free parameter,  $x_t$  and  $x_s$  are the vectors in low dimensional feature space [32].

$$kf(x_t, x_s) = e^{-\frac{(x_t - x_s)^2}{2\sigma^2}} \quad (6)$$

## 4.3. ANN

Artificial Neural Network (ANN) is one of the prominent ML techniques used for classification problems. It contains three layers, namely input, hidden, and output layers. The input data feeds the input layer, where the neurons hold those values. Hence, it processes this data to neurons in the hidden layers. There can be one or more hidden layers in ANN. The value of each hidden neuron ( $k$ ) of hidden layer  $m$  is calculated using formula (7).  $L$  is the input neuron value, and  $W$  is the weight of the connection between input and hidden neurons. The hidden layer is responsible for performing the activation function, namely, the logistic sigmoid function on the hidden neurons given in formula (8). Like the hidden layer, the values of output layer neurons are calculated using formula (9), where  $HA$  is the activation value of the hidden neuron. Then the activation values of output neurons are obtained using the activation function in formula (10). This activation function will determine the output value, which is between 0 and 1. [33]

$$H_{km} = \sum L * W \quad (7)$$

$$HA_k = \frac{1}{1 + e^{-H_k}} \quad (8)$$

$$O_k = \sum HA * W \quad (9)$$

$$OA_k = \frac{1}{1 + e^{-O_k}} \quad (10)$$

## 4.4. Extreme Learning Machine (ELM)

ELM is a feed-forward neural network which can be used for classification purpose. It has only one hidden layer so it can be called a single hidden layer feed-forward neural network. The training speed of ELM is very less when compared to an artificial neural network. ELM contains only a single input, hidden, and output layers. It doesn't use a back propagation technique like ANN. Instead, it uses an inverse matrix concept. It calculates an output weight matrix based on which the prediction is made. A detailed stepwise algorithm for ELM was demonstrated below.

In step 2, the input neuron values are given based on input instances. Assigning random values to the input layer's weights and bias for the hidden layer neurons occurs in step 3. In step 4, the output matrix for the hidden layer is calculated. Formula (11) is the general output function used to calculate each element of matrix  $H$  in formula (12). The activation function in this step is usually the sigmoid function. The matrix  $H$  from this step is used to calculate the weight matrix for the output layer in step 5. Here formula (13) is for obtaining the output weight matrix, and formula (14) is its matrix representation. The matrices  $H$  and  $\beta$  from steps 4 and 5, correspondingly, are used to calculate the output values in step 6. The formula (15) is to calculate the output matrix with predicted target values. Formula (16) is the matrix representation of  $T$ . To conclude, from this matrix  $T$ , the predicted values are given as output for the given input instances [34].

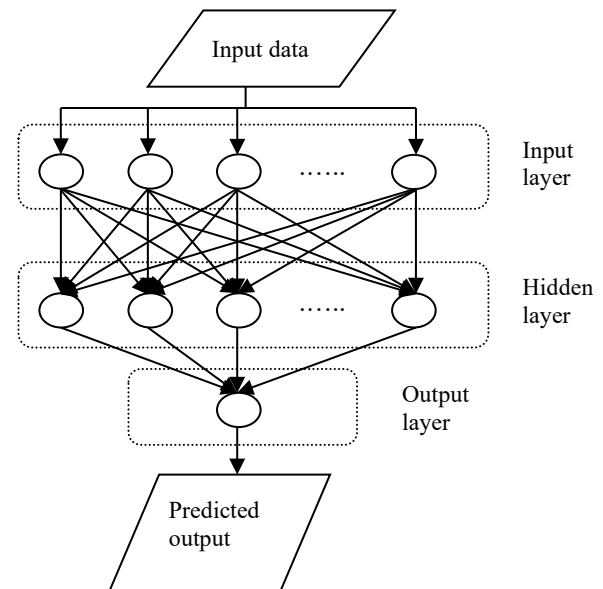


Figure 4. Schematic diagram of ELM

**Algorithm: Extreme Learning Machine (ELM)**

INPUT: Give the dataset as input

OUTPUT: Predicted output values for the given input instances

ASSUMPTIONS:  $k$  is total instances,  $x_k$  is the input vector,  $h_t$  is the output value for hidden neuron  $t$  where  $t = 1, 2, \dots, p$ ,  $b_t$  is the bias of the hidden neuron  $t$ ,  $w_t$  is weight vector for connections between the input layer and the hidden layer neurons  $t$ ,  $\beta$  is weight vector connecting neurons of the hidden layer, and output layer,  $g()$  is the activation function.

STEPS:

1. Start
2. Set the input layer neuron values with the input instances.
3. Randomly assign input layer weights and hidden layer neurons biases.

4. Calculate the output matrix for the hidden layer.  
 $h_t = g(w_t * x_k + b_t)$ , where  $k = 1, 2, \dots, n$  (11)

$$H = \begin{bmatrix} g(w_1x_1 + b_1) & \dots & g(w_px_1 + b_p) \\ \vdots & \ddots & \vdots \\ g(w_1x_n + b_1) & \dots & g(w_px_n + b_p) \end{bmatrix} \quad (12)$$

5. Obtain output layer weight matrix, the pseudo inverse of  $H$ . Here  $D$  is the matrix containing actual target values from the input instances.

$$\beta = (H * H^T)^{-1} H * D \quad (13)$$

$$\beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_p \end{bmatrix} \quad (14)$$

6. Calculate output for the input instances.

$$T = H * \beta \quad (15)$$

$$T = \begin{bmatrix} t_1 \\ \vdots \\ t_p \end{bmatrix} \quad (16)$$

7. Return the predicted output values.

8. Stop

The pictorial representation for the generalized process of the algorithm is demonstrated in figure 4. After providing the input, values to the input layer neurons are assigned. Weights and biases are assigned randomly, as explained in the above algorithm. Hidden layer neurons connected to input neurons are used to obtain the output matrix for the hidden layer. The final matrix for the output layer was obtained using this matrix, which gives the predicted values.

**5. Metrics and definitions to evaluate results**

Accuracy, 0-1 loss, TS or CSI, FOR, and FDR evaluation metrics are considered in this work. This section comprises of definitions of metrics. Evaluation of each metric for the best algorithm is discussed in section 6.

**Accuracy**

This metric is used to calculate the percentage of instances that are classified correctly. Accuracy was calculated based on formula 1.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \quad (1)$$

**Zero One Loss (0-1 Loss)**

It is an evaluation metric that is used to calculate the misclassification rate. Its value usually lies between 0 and 1. The value nearer to 0 is considered as a good value and can be said as best performance.

**TS or CSI**

Threat Score (TS) or Critical Success Index (CSI) is an evaluation metric that is defined as the ratio of no. of instances which are correctly predicted as positive to the total no. of instances except the correctly predicted negatives. Its value lies between 0 and 1. The highest value represents good value.

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

**FOR**

FOR stands for False Omission Rate that is calculated using parameters of the confusion matrix. It is defined as the ratio of no. of instances wrongly predicted as negative to the total no. of instances which are predicted as negative. Its value lies between 0 and 1, where the value nearer to 0 represents a good value.

$$FOR = \frac{FN}{FN + TN} \quad (3)$$

**FDR**

FDR stands for False Discovery Rate that is calculated using confusion matrix parameters. It is defined as the ratio of no. of instances wrongly predicted as positive to the total no. of instances that are predicted as positive. Its value lies between 0 and 1, where the least value represents good value.

$$FDR = \frac{FP}{FP + TP} \quad (4)$$

**6. Results analysis & discussion**

The results obtained by implementing algorithms in R programming are provided in this section. The analysis of results was done and also discussed here. The demonstration of each metric is given for the proposed technique extreme learning machine (ELM). The existing algorithms were also evaluated in the same way. The values of TP, TN, FP and FN from the confusion matrix obtained for ELM are 19, 6, 1, and 0 in that order. Using these values, some evaluation metrics can be calculated as in the following subsection.



## 6.1. Evaluation metrics

Evaluating proposed technique ELM using all the considered evaluation metrics is demonstrated below. These metrics are defined in section 5. In this work, the value of 0-1 loss is obtained by implementing a built-in function in R programming. The 0-1 loss value obtained for ELM is 0.0385. This value indicates better performance of ELM in terms of 0-1 loss. In addition, remaining four metrics had also obtained better results as per the respective criteria.

Accuracy of ELM =  $(19+6) / (19+6+0+1) = 0.9615 = 96.15\%$

TS value of ELM =  $19 / (19+0+1) = 0.95$

FOR value of ELM =  $0 / (0+6) = 0$

FDR value of ELM =  $1 / (1+19) = 0.05$

## 6.2. Results obtained

After implementing all the considered algorithms, the results obtained using same data set described in section 3 are given below. The values of five evaluation metrics for each considered algorithms KNN, SVM, ANN and ELM are provided in tables 2, 3, 4, and 5. The ANN and ELM are neural network techniques. In this work, the no. of neurons considered in the hidden layer is 10 and 35 for ANN and ELM, respectively. Two neural network techniques can be compared using cross-entropy error (log loss) values. Cross entropy error or log loss is a metric that is used to measure the classification model performance only when the output is given as probability value, i.e., range [0, 1]. These predicted probabilities are rounded up to obtain the confusion matrix for calculating the above evaluation metrics. The value of cross-entropy error increases when the predicted probability doesn't match the actual value or label. Less value represents good performance, and a value equal to 0 indicates the best performance. The log loss value for the neural network techniques considered in this work is also obtained. By comparing them, it was found that the proposed technique ELM has obtained the least value of 1.3285 and outperformed ANN, whose value is 5.31375.

Table 2. Results of KNN

Accuracy (%)	0-1 Loss	TS/CSI	FOR	FDR
84.62	0.1538	0.8095	0.375	0.5556

Table 3. Results of SVM with Gaussian kernel

Accuracy (%)	0-1 Loss	TS/CSI	FOR	FDR
92.31	0.0769	0.9048	0.1667	0.05

Table 4. Results of ANN

Accuracy (%)	0-1 Loss	TS/CSI	FOR	FDR
84.62	0.1539	0.8095	0.1667	0.15

Table 5. Results of ELM

Accuracy (%)	0-1 Loss	TS/CSI	FOR	FDR
96.15	0.0385	0.95	0	0.05

The comparison of all the algorithms in terms of each metric is demonstrated in figures 5 and 6. The existing algorithm values are presented using blue color, and ELM technique values appear in orange color. From the figure, it was clear that the proposed technique ELM has outperformed the existing algorithms in every metric. It was identified as the best performing one among all, with values of 96.15%, 0.0385, 0.95, 0, and 0.05 for accuracy, 0-1 loss, TS/CSI, FOR, and FDR, in that order.

The comparison of proposed work with similar literature works is demonstrated in table 6. Most of the literary works are performed based on various machine learning algorithms. Each work operates on a different dataset. In this context, for the considered dataset, some of the algorithms from the literature are considered and applied to it. The works [19, 21, 22, and 24-29] included the SVM technique, which was identified as the best performing algorithm in some works. The algorithm KNN was used in [19, 22, and 26], and ANN was used [24 and 26]. These are the techniques considered from previous research works, and after obtaining the results, the performance of those existing ML algorithms is compared with the new proposed algorithm ELM. Present and previous works are based on the ML techniques but present work used ELM also. The previous articles did not address the ELM algorithm. Figures 5 and 6 show that ELM outperformed the remaining techniques. Hence, it was clear that ELM will help predict DFU more accurately than other similar algorithms from literary works.

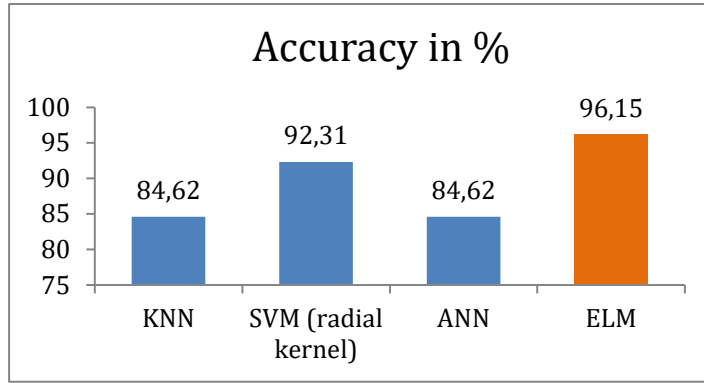


Figure 5. Comparison of algorithms in terms of accuracy

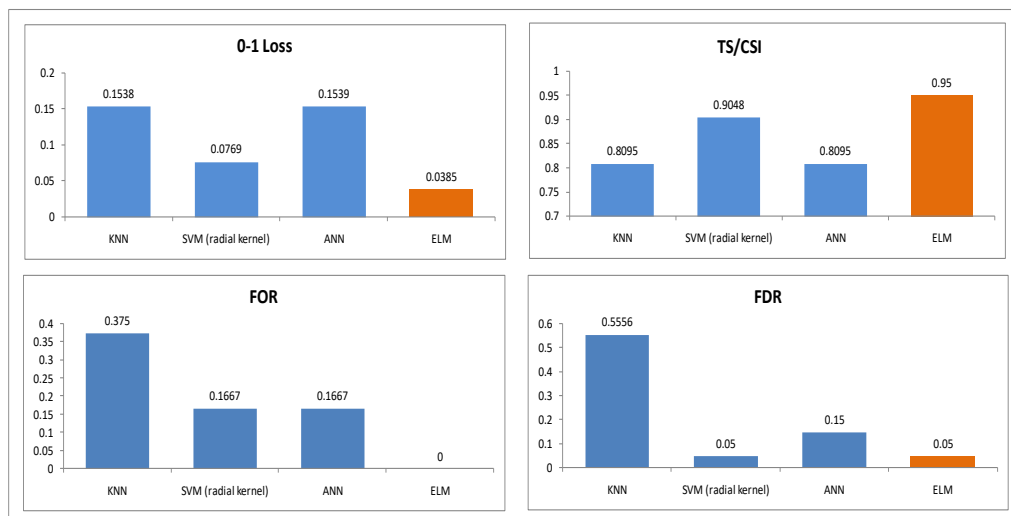


Figure 6. Bar graphs for comparison of algorithms based one evaluation metrics

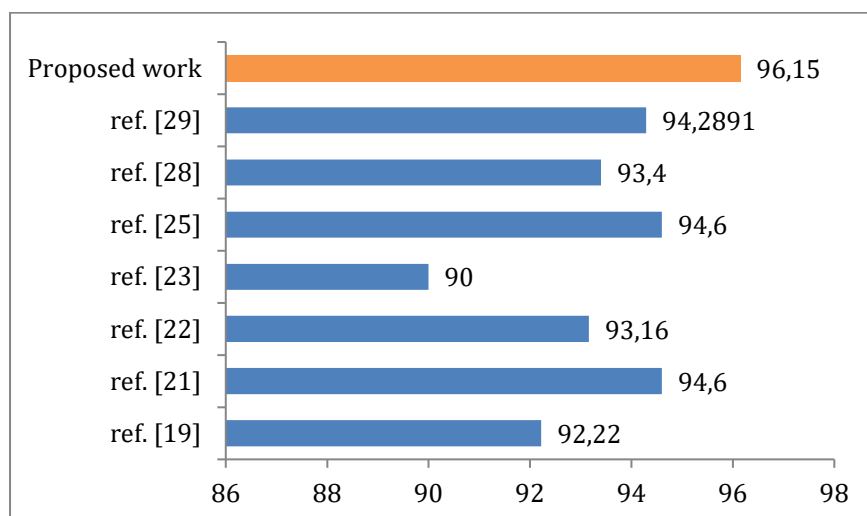


Figure 7. Comparison of literature work and proposed work on the basis of accuracy

Table 6. Comparing proposed work with similar literature work

Work by authors	Algorithms chosen	Findings	Identified best algorithm	Results obtained
Authors of this work	SVM with Gaussian kernel, ANN, KNN, and Extreme learning machine (ELM)	Predicted diabetic foot ulcers using ML classification techniques. ELM is the proposed algorithm which is compared with existing algorithms ANN, KNN, and SVM with Gaussian kernel. Evaluation and comparison is performed based on accuracy, 0-1 Loss, TS/CSI, FOR and FDR.	Extreme learning machine (ELM)	Accuracy=96.15% 0-1 Loss=0.0385, TS/CSI=0.95, FOR=0 and FDR=0.05
Pushpalela et al. [19]	SVM, naive Bayes, KNN, C4.5 and decision tree	Used some classification techniques to predict diabetic foot ulcers in type-2 diabetic patients. All the algorithms are evaluated and compared depending on the accuracy obtained.	SVM	Accuracy=92.22%
Sudarvizi et al. [21]	SVM	The implemented SVM algorithm on the data obtained from load cell sensors inserted in the foot mat. Evaluated results using accuracy and precision metrics.	SVM	Accuracy=94.6% and Precision=95.2%
Adam et al. [22]	Decision tree, probabilistic neural network, SVM with Gaussian kernel, KNN, LDA and QDA	Detection of DFU in patients with and without neuropathy was performed using ML techniques on the hospital dataset. KNN employed with locality sensitive discriminant analysis feature reduction is the technique suggested from work. Accuracy, sensitivity, and specificity are metrics used for evaluation.	KNN employed with locality sensitive discriminant analysis feature reduction technique	93.16%, 90.91% and 98.04% of accuracy, sensitivity and specificity respectively
Goyal et al. [23]	Ensemble CNN with super pixel colour descriptor	A computer vision technique was proposed to diagnose ischaemia and infection separately in the patients of DFU. The proposed technique was implemented on image dataset. This technique was evaluated based on accuracy.	Ensemble CNN with super pixel colour descriptor	Accuracy=90% for ischaemia and Accuracy=73% for infection.
Wang et al. [24]	SVM, ANN and cascaded 2-stage SVM based classification	The area of DFU was determined by using cascaded 2-stage SVM based classification and compared it with two other ML techniques. Sensitivity and specificity are considered for evaluation purpose.	Cascaded 2-stage SVM based classification	73.3% sensitivity and 94.6% specificity respectively.
Botros et al. [25]	SVM	Considered the problem of predicting diabetic foot ulcer in non diabetic, diabetic with diabetic peripheral neuropathy (DPN) and diabetic without DPN patients. The dynamic plantar pressure measurements were considered for prediction. Accuracy, precision and ROC are the metrics chosen for evaluation purpose.	SVM, as only one algorithm was chosen.	Obtained precision, ROC and accuracy of more than 95.2%, 0.946 and 94.6% respectively in case of all the three cases.
Patel et al. [26]	KNN, SVM, fuzzy logic, Bayesian networks and neural networks	Medical image processing is considered for developing a wound detection system for DFU. The image pre-processing, image segmentation, feature extraction & texture detection and image classification are the four steps performed to classify the wound into three groups slough, necrotic and granulation.	The comparison of algorithms was not performed.	The results are not obtained in terms of evaluation metrics. Only cluster of images for each group were provided.

Keerthika et al.[27]	Watershed, region growth algorithm with single stage SVM	Prediction of DFU is done on the basis of image segmentation using watershed and region growth algorithms. Then SVM is used for classification of the image and identify whether it is in initial or final stage.	Watershed, region growth algorithm with single stage SVM.	No metrics are considered for evaluation. Only the prediction of initial or final stage of DFU was done.
Cui et al. [28]	Patch-based CNN, SVM and U-net	Diabetic wound segmentation was done mainly on the basis of CNN. The steps involved are pre-processing followed by image segmentation using patch-based CNN and then post-processing. It was compared with SVM and U-net in terms of precision, sensitivity, specificity, pixel accuracy, mean IoU, dice and MCC.	Proposed patch-based CNN performed better than SVM. U-net performed better than CNN but there is no vast difference among them.	CNN: Values obtained for precision, sensitivity, specificity, pixel accuracy, mean IoU, dice and MCC are 0.722, 0.9, 0.947, 0.934, 0.660, 0.770 and 0.753 respectively.
Veredas et al. [29]	BCM, EACM, SVM and multiclass BCM.	Identified tissues in the wound images. Region segmentation was performed using mean shift and region growing techniques followed by proposed BCM and EACM techniques with heuristic approach. These are compared with other similar ML techniques SVM and multiclass BCM in terms of accuracy, success, sensitivity and specificity.	EACM with heuristic approach	Obtained an overall sensitivity=85.722 8%, specificity=96.430 7%, success=91.0767 % and accuracy=94.289 1%.

Some works in literature used image classification algorithms like BCM, EACM, and CNN. As the dataset chosen in this work was a clinical dataset but not an image dataset, those algorithms were not considered here. From the comparative study, it was observed that the ELM algorithm achieved very good values in each and every metric. Apart from KNN and SVM with Gaussian kernel, ANN and ELM are the neural network techniques. The advantage of using ELM over ANN was provided above table 2. Various literature works which have used accuracy for evaluation purpose are compared with the proposed technique in figure 7. This comparison ensures to identify the work which got highest accuracy. Though datasets used are different the overall accuracy of literature works are less compared to ELM in the proposed work. This exhibits the effectiveness of proposed DFU prediction model.

Pangaribuan et al. [35] have considered ANN and ELM algorithms for diagnosing diabetes. Their work is focused on comparing only ANN and ELM in diabetes and mean squared error (MSE). A foot ulcer is one of the complications of diabetes. An efficient model was developed in the present proposed work to diagnose diabetic foot ulcers to avoid diabetes consequences and its other side effects. Comparisons encompassed ELM with ANN and two other prominent ML techniques, KNN and SVM with Gaussian kernel. By performing this comparison, ELM performed better than KNN and SVM

(Gaussian kernel) in addition to ANN. The scope of comparison was increased. And different metrics related to identifying the loss rate or error rate were chosen for analysis and accuracy. These facts differentiate this paper from other works like research work in [35]. As ELM outperformed remaining techniques, including ANN, it was recommended over the other methods.

## 7. Future work

Accuracy of 96.15% is obtained by the proposed approach which refers to best output. Enhancing the output by considering the dataset with some extra attributes related to diabetic foot ulcer will be considered for future work. In addition, evaluating different classification techniques based on some prominent metrics, the association between diabetes and its complications will be considered. It is recommended that more such works should concentrate and obtain better techniques to predict foot ulcers and other diabetic related side effects and risks. It is also hoped that future works will emerge that concentrate on Corona effects for diabetic patients also using latest effective novel Machine learning methods.

## 8. Conclusion

Diabetes is a disease that most people are suffering from across the world. As diabetic foot ulcer disease is a significant complication of diabetes, its accurate prediction is crucial. After predicting it early, immediate treatment could save the diabetic patient from losing any leg part. A practical model relying on the best out of four considered ML techniques besides information from related works helped achieve accurate diabetic foot ulcer prediction. By evaluating the performance of the considered algorithms, it is found that ELM obtained better values of 96.15%, 0.0385, 0.95, 0, and 0.05 for accuracy, 0-1 loss, TS/CSI, FOR, and FDR, respectively. Among these techniques, the proposed technique extreme learning machine (ELM) has achieved better results than the remaining methods. Hence, it is recommended to use ELM to predict diabetic foot ulcers.

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