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AI-Based Intelligent System for Healthcare Application Using Edge-Based Neural Random Back Propagation Technique

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Abstract: The rising prevalence of diabetes, driven by dietary changes and reduced physical activity, is a leading cause of mortality worldwide. Early diagnosis is critical to managing this chronic condition. This study proposes an AI-based intelligent system for early diabetes detection using Edge-Based Neural Random Backpropagation (EB-NRBP). The EB-NRBP model leverages feature selection via the Least Absolute Shrinkage and Selection Operator (LASSO) to enhance the regularization of the classification process. This approach optimizes the classifier's cost function and accelerates its development through Random Forward Gradients in conjunction with Edge-Based neural networks. The model's performance was compared with conventional methods, demonstrating a significant improvement in classification accuracy. The EB-NRBP model achieved a high success rate of 98%, outperforming traditional techniques in terms of efficiency and precision. This AI-based system presents a promising solution for the early diagnosis of diabetes, offering higher accuracy and faster detection compared to existing methods. It holds potential for integration into healthcare applications, enhancing early intervention and improving patient outcomes.

Keywords: Intelligent system, Information and communication technology (ICT), World Health Organization (WHO), Diabetes, Artificial Intelligence (AI), Least Absolute Shrinkage and Selection Operator (LASSO), Edge Based neural Random back propagation (EB-NRBP).

1. Introduction

Investigators and the healthcare industry have been interested in Artificial Intelligence (AI) because of its capacity to handle vast volumes of data, create precise findings, and regulate operations to achieve the best possible result. Since robots are employed to make decisions and forecast the long-term repercussions of illnesses, an intelligent system isn't a new concept. Robots and analytics aid most daily chores in today's environment. Dependable computer results consider several aspects: justice, interpretability, responsibility, dependability, and acceptability [1]. The consensus is that AI technology will assist and augment it rather than completely replace human workers, such as that performed by physicians and other healthcare professionals. Medical personnel may benefit from AI's aid with various tasks, including admin tasks, health records, client engagement, and specialized expertise in image analysis, managing medical devices, and providing care [2]. According to the WHO, diabetes affects 422 million individuals worldwide, making it one of the most prevalent illnesses among people. The percentage of individuals with diabetes patients now accounts for 8.5% of the total, up from 4.7% in 1980 due to changed food patterns and a lack of physical activity. Additionally, 1.1 million young people and teenagers are thought to have diabetes. Diabetes kills approximately 4 million individuals worldwide per year. Diabetes is a genetic condition. Thus, its effects extend beyond the person who has them to the subsequent generation. According to WHO, the global cost of treating diabetes was nearly 850 billion US dollars in 2017 [3]. Dentistry has made significant progress because of developments in artificial systems and equipment. Information Technologies (IT) have been established specifically for dentistry specialties, and dental-related products still need specialized research. Dentists and physicians can access a patient's health information using standardized dental software. It might be argued that AI is heavily used in illness detection with reliability on par with medical professionals [4]. A new age of effectiveness and imagination in the medical field has been brought about by the incorporation of AI.

The potential of based on AI machines to improve evaluation, therapy, and general support for patients through the use of modern computer science is revolutionary for medical devices. The combination of AI with hospitals has huge potential to improve the efficacy, availability, and overall level of medical supplies in a time when technology developments remain crucial. It is evident from the explanation above that treating diabetes early may help individuals save quite a lot of expenses and shield them from contracting other serious illnesses. Many academics have employed machine learning techniques in recent years to diagnose diabetic illness by comprehending connections derived from risk variables [5]. Figure 1 represents the role of AI in the healthcare industry.

The following are the primary contributions made by this paper:

- To provide an AI-based intelligent system using Edge-Based Neural Random back propagation (EB-NRBP) for diagnosing early disease.
- Least Absolute Shrinkage and Selection Operator (LASSO) is used for feature selection in the EB-NRBP classification technique to improve regularization.
- To lower the cost function of the classification in the EB-NRBP, an unrestricted optimal design is used.
- To stimulate the growth of the classifier, random forward gradients are also combined with edge-based neural networks.

The remaining article is structured as follows: The latest status of the works on the classification of diabetic illness is summarized in Section 2. Section 3 presents the suggested model. Section 4 discusses the experiment's findings, and Section 5 covers conclusions and future studies.

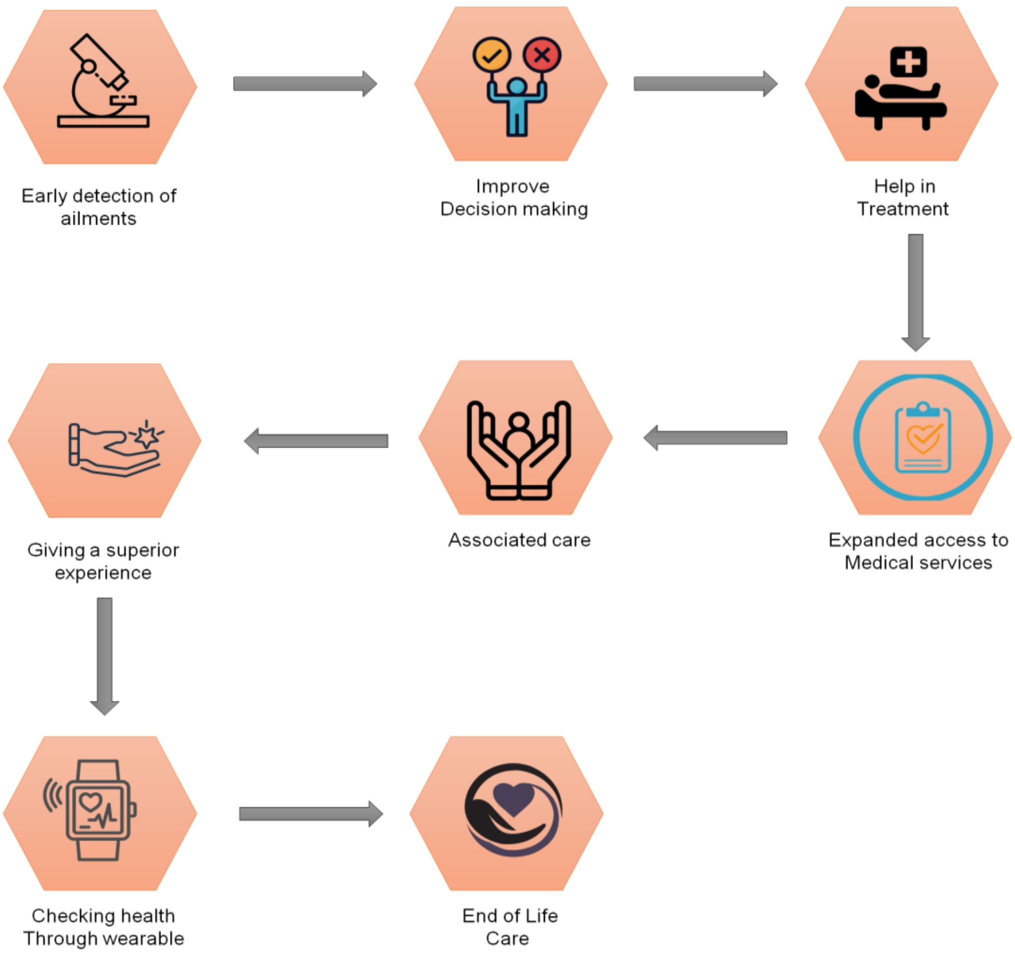

Figure 1. Role of AI in healthcare

2. Literature Review

They suggested an effective and precise approach to diagnose cardiac disease in the paper [6], and the system is founded on machine learning methods. The system's classification methods involve Decision trees, K-nearest neighbors, Logistic regression, Artificial Neural Networks (ANNs), and Support vector machines. Standard feature selection algorithms like Reliever, Limited backup maximum possible significance, least squares wastage capable of evaluating, and Local learning have been used to remove unnecessary and redundant features from the . The research [7] described that applications for mobile healthcare could assist patients with diabetes management, lower the likelihood of issues, improve controlling diabetes, and enhance results for patients. This comprehensive investigation aimed to ascertain the degree of application acceptance amongst patients with the condition, pinpoint the variables linked to application deployment and utilization, and investigate patients' viewpoints about applications and the most often desired characteristics. They provide a thorough overview of "AI-based Modeling" in the paper [8] along with the precepts and functionality of potential AI techniques that could be crucial in the development of intelligent and smart systems in a variety of real-world various applications, such as corporate, financial services, healthcare, agricultural production, smart cities, information security, and many others. Additionally, they underline and underline the academic concerns relevant to their. The study [9] proposes using Density Feature Selection (DFS) combined with Ant Colony Optimization (D-ACO) for chronic kidney disease (CKD) to enhance healthcare forecasting and classification DFS-ACO method may not generalize well across diverse datasets. A study suggests a recurrent neural network (RNN) based on a wearable sensor-based system for movement forecasting on an end device [10]. The system's input data comes from wearable healthcare sensors, including magnetic, altimeter, gyroscope, and electrocardiography (ECG) detectors. An RNN is then taught using the characteristics. The RNN that has been taught is then employed to forecast the events. They suggest in perspective [11] that the reasoning is a misplaced expectation for understandable AI and that the objectives for patient-level decision assistance are unlikely to be reached by existing explain ability techniques. A limitation of this study is the challenge of explainability in AI models, particularly the EB-NRBP system. While the model achieves high performance, its "black-box" nature limits the ability to explain individual decisions, potentially hindering trust and adoption in clinical settings without significant advances in explainable AI methods.

They outline current modeling and analysis strategies and highlight how different failure instances might make it difficult for patients to make decisions. A fuzzy logic and cuckoo search algorithm (CSA) reductions classifiers are methods for diabetes prediction that the authors have suggested in [12]. A limitation of this study is the lack of validation for the diagnostic model in identifying diseases other than COVID-19. While the system demonstrates high accuracy in distinguishing COVID-19 cases, its performance may be compromised when diagnosing conditions with similar pulmonary symptoms, limiting its generalizability.

The suggested method consists of two parts. The initial steps involve reduction in feature, accomplished using a CSA to identify associated properties would decrease the number of features and eliminate extraneous or noisy data. The creation of fuzzy rules occurs in the second stage, after which the diabetes illness is classified using these criteria. They evaluate various information systems in article [13]. A limitation of this study is that it primarily focuses on fog computing as an alternative to cloud computing for real-time IoHT (Internet of Healthcare Things) applications, without exploring the scalability challenges or the integration complexities with existing healthcare infrastructures. Additionally, practical implementation in diverse, real-world healthcare environments remains underexplored.

They next offer a framework app based on fog computing. Additionally, they draw attention to the challenges and possible applications of integrating computational fog technology with the Internet of Things medical facilities. The results of the investigation pointed out those IoT systems that utilize computational fogging have great potential. In the research [14], they developed an Artificial Neural Network (ANN)-based AI system for illness prediction. The ANN's regularization increased the accuracy of the classification model. To get the cheapest price, the unconstrained optimization model lowered the cost function of the classifier. The primary goal of the study [15] was to investigate the possible uses of big data analytics and computer continuous learning techniques in people with diabetes. The data analysis suggests that the suggested ML-based system can score 86. Health experts, as well as other relevant individuals, aim to develop categorization models that will help them diagnose diabetes and develop preventive actions. A limitation of this study is the use of a structured dataset for training the machine learning models, while unstructured data was not considered. Future work could explore the integration of unstructured data and include additional attributes such as family history, smoking habits, and physical inactivity for more comprehensive diabetes prediction.

From a managerial standpoint, several computational techniques (CI) healthcare implementations and the difficulties they provide have been briefly summarized in section [16]. A limitation of this study is the focus on energy efficiency within residential buildings using machine learning, without considering broader applications in other sectors.

Table 1. Literature Overview

Study/Method	Contribution	Method	Results	Limitations	Future Direction
[6] Cardiac Disease Diagnosis	Proposes a machine learning-based system for diagnosing cardiac disease.	Decision Trees, K-NN, Logistic Regression, ANNs, SVM	High accuracy with multiple classifiers, but no specific performance metrics given.	No performance comparison among classifiers; lacks feature importance analysis.	Incorporate feature importance and explainability methods (e.g., SHAP, LIME).
[7] Mobile Healthcare for Diabetes Management	Investigates mobile health app acceptance and its impact on diabetes management.	Survey-based study, statistical analysis	High patient satisfaction and willingness to use mobile healthcare apps.	Limited to patient-reported data; lacks clinical validation.	Implement clinical trials to validate the app's effectiveness in real settings.
[8] AI-based Modeling for Smart Systems	Overview of AI techniques for smart systems across various sectors.	General AI modeling techniques for healthcare, agriculture, etc.	AI techniques could enhance real-world systems in diverse sectors.	Broad scope with no focus on specific healthcare applications.	Narrow focus on healthcare applications, especially for early disease diagnosis.
[9] chronic kidney disease (CKD) Forecasting	Proposes DFS and D-ACO for CKD classification and forecasting.	Density Feature Selection (DFS), Ant Colony Optimization (D-ACO)	Improved CKD prediction accuracy using feature selection.	Limited to a specific disease; no real-time application.	Integrate real-time data collection and prediction in clinical settings.
[10] Wearable Sensor-based Movement Forecasting	Proposes RNN-based movement forecasting for healthcare applications.	Recurrent Neural Network (RNN)	Achieves accurate movement forecasting using sensor data.	Requires continuous sensor input, potentially limiting scalability.	Explore integration with IoT devices for real-time monitoring.
Random Forests	Uses Random Forests for high-accuracy classification.	Random Forests (RF)	Good accuracy but computationally expensive.	High computational cost, especially with large datasets.	Optimize computational efficiency using hybrid models.

Future research should expand the application of machine learning to various industries and explore additional ways to optimize resource consumption and minimize waste across different systems. The usage of CI has been shown to reduce errors in healthcare tasks compared to humans in several situations. Several practical challenges will hamper the large-scale automation of CI in healthcare. The research [17] was marked from persistently elevated levels of blood sugar because of insufficient insulin synthesis from the pancreas. An intelligent system for tracking diabetes patients using methods of machine learning is shown in the paper [9].The architectural components comprised smart gadgets, cameras, and cellphones to gather waist measurements. The intelligent system gathered the patient's data, which then used machine learning to classify the information to establish a diagnosis. Within the field of medicine, technologies are evolving to give clients efficient immediate support [18]. The number of health problems and disorders amongst individuals is drastically increasing in today's situation. As a result, at hospitals and clinics having not enough room and medical capabilities, there is getting harder to receive and treat more new cases. The research [19] discovered the late diabetics' neuropathy a neurological condition related to insulin mellitus can result in significant impairments, illness, and death. A clever tool that combines three well-proven techniques to effectively test potential diabetes neurological conditions. Table 1 presented the Summary of the literature review.

2.1 Problem Statement

Diabetes is a rapidly growing global health concern, with increasing prevalence due to changes in lifestyle, diet, and reduced physical activity. Timely and accurate diagnosis is critical to prevent complications such as heart disease, kidney failure, and nerve damage. However, current diagnostic methods often lack efficiency, leading to delayed detection and treatment. Traditional techniques may also struggle to handle large, complex datasets, impacting diagnostic accuracy. This study aims to address the challenges of early diabetes detection by leveraging advanced AI techniques. Specifically, the proposed system uses Edge-Based Neural Random Backpropagation (EB-NRBP) with Least Absolute Shrinkage and Selection Operator (LASSO) for feature selection. The objective is to enhance classification accuracy while reducing the computational complexity of diabetes prediction. The focus is on improving diagnostic speed and precision by utilizing random forward gradients in the EB-NRBP model. The model's performance will be compared to conventional methods to validate its superiority in accuracy. By optimizing the early detection process, the system could contribute significantly to better management of diabetes, reducing long-term health risks and improving patient outcomes. The transformative potential of AI-driven solutions in healthcare diagnostics, particularly in the early detection and management of diabetes. By integrating advanced techniques such as Edge-Based Neural Random Backpropagation (EB-NRBP) and feature selection with Least Absolute Shrinkage and Selection Operator (LASSO), the study seeks to enhance diagnostic accuracy and efficiency. The proposed approach offers a more precise, timely, and scalable solution for diabetes cares, ultimately improving patient outcomes and optimizing healthcare delivery.

3. Methodology

Recent developments in AI technology have resulted in affordable methods for healthcare-related applications that use a wide range of sensors and computers. Information systems (IS) are highly sophisticated devices that detect and interact with their environment. Inadequate insulin levels in the blood are the primary reason for persistent hyperglycemia in people with diabetes. Insulin control, glycogen synthesis, cell cycle, advancement, and the hypertrophic maintenance of fats and proteins depend on insulin. The effectiveness of the suggested system is examined here (EB-NRBP). We have gathered and preprocessed the data. The suggested methodology flow has been illustrated in Figure 2.

3.1 Sample collections of data

Data for the Saudi Diabetes Mellitus (DM) categories database was collected among the King Fahad University Hospital (KFUH) which was located Khobar, Eastern Province, Saudi Arabia.

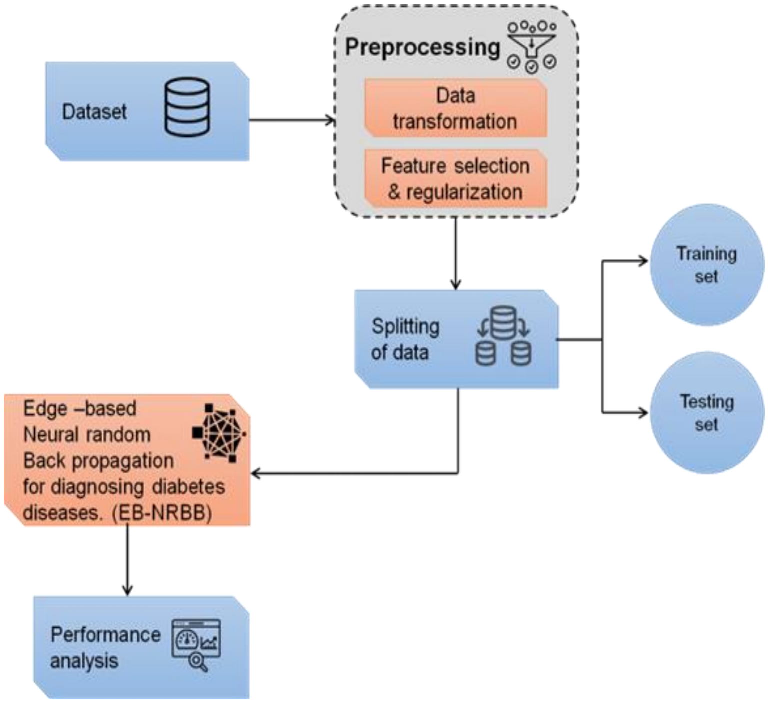

Figure 2. The workflow of the suggested algorithm

Table 2. Dataset characteristics

Feature	Description
Gender	Male or Female.
Tg	Patient's blood triglyceride concentration.
A1c	The glycated hemoglobin provides a measure of the amount of glucose that has bonded to the hemoglobin gene within the blood.
Albumin	The quantity of proteins synthesized in the liver.
LDL	The quantity of harmful cholesterol is represented by low-density lipoprotein.
Insulin	To counteract the insulin hormone produced by the islet cells within the pancreas, an exogenous injected version of insulin is administered.
AntiDiab	Diabetes prevention refers to a blood sugar-lowering oral medicine.
Nutrition	if the diet being followed is appropriate or not.
Injectable	It is decided whether to utilize the medication liraglutide.
Outcome	Pre-diabetes, T1DM, and T2DM are the three kinds included in the target class.
Education	If they have been taught to take care of themselves or not.

A total of 897 inpatients were included, with 731 having prediabetes, 89 having type 1 diabetes, and 77 having type 2 diabetes; the report consists of 10 distinct characteristics. No identifying information, such as patient names or contact numbers, was included to protect their identity. The study's dataset [20] characteristics are described in table 2.

3.2 Data preprocessing

As a subset of collected data, data preprocessing refers to any operation carried out on unprocessed data to create it suitable for further data analysis. It may also describe removing or changing information before applying it to achieve a desired result. It is used on the information gathered. As a first step, we apply min-max normalization to transform the data. It reduces duplication and enhances authenticity, which promotes execution speed. In addition, the LASSO method may be used to select features.

3.2.1 Data transformation and Missing values

One of the most popular approaches for data normalizing is called min-max normalization. Such normalization is used in the process of data transformation. When given a maximum and a minimum value for a numeric feature, it adjusts the result to fulfill the needs of its users. Data transformation in the medical system may be identified by the expression (1).

$$Min - Max = \frac{(A - A_{min})}{(A_{max} - A_{min})} \tag{1}$$

Here A is a collection of the predicted values represented in the dataset.

Missing values in the diabetes dataset were handled using imputation techniques. Specifically, missing data points were filled using the mean or median of respective features, depending on their distribution. This approach prevents loss of data and ensures the model remains robust without introducing bias, improving the accuracy and reliability of the Edge-Based Neural Random Backpropagation (EB-NRBP) model. Proper handling of missing values is essential for achieving optimal model performance.

3.2.2 Selection of feature using Least Absolute Shrinkage and Selection Operator (LASSO)

The LASSO approach is a valuable tool for both regularization and feature selection. Regularization is a technique for decreasing failures and preventing training errors. Actual variable ratings are produced in the LASSO approach, and then a restriction is placed on specific values so that their aggregate must be smaller than a maximum limit value. Therefore, the approach employs a regularization phase, during which some of the predictive variables' coefficients are updated to zero. In the feature selection phase, only those features are evaluated for inclusion. Achieving high-quality accuracy by minimizing training errors is simple by using the LASSO approachand selected features include Tg, A1c, LDL, Insulin, and AntiDiab, which are crucial for predicting diabetes outcomes like pre-diabetes, T1DM, and T2DM. Other features are excluded.

The LASSO approach, that additionally lessens estimation differences, serves to choose the parameters. When there's multiple elements although little data can be obtained through the specimens, extrapolation shrinking can be utilized. If and only if the total actual worth of the parameters exceeds then a constant of some sort, this method permits a portion of the components to see their values lowered to nothing by reducing the total value and the squared amounts to form a leftover, a process equivalent to reducing the length of the summation of the squared values given as a constant condition $\sum_j |\beta_j| \leq P$. Through adding an expense to the optimizing manages, the approach uses regularization of L 1 to maximize the goal. The outcome shows the factors that have decreased and by the %, and it is computed using the real amounts of the components. The LASSO value might be attributed as shown in (2).

$$\delta_{Lasso} = \frac{minimum}{\delta}\left(\sum_{a=1}^{k}\left(u_i - \sum_q \delta_q V_{ij}\right)^2 + \Gamma \sum_q |\delta_q|\right) \quad (2)$$

Γ Represents a shrinkage percentage. The weighing procedure which is applied to all variables is given by formula 3.

$$\delta_{ModifiedLASSO} = \frac{minimum}{\delta}\left(\sum_{a=1}^{k}\left(u_i - \sum_q \delta_q V_{ij}\right)^2 + \Gamma \sum_{q=1}^{m} \widehat{W}_f |\delta_q|\right) \quad (3)$$

Where a was an indication of important, $|\widehat{and\,\delta_f}|$ represents the δ variable's initial estimation, and is the δ variable's initial projection, where w_f is a weighting function defined as $w_f = \frac{1}{|\hat{\delta}_f|^{\alpha}}$. Algorithm 1 explains LASSO methodology.

Algorithm 1. LASSO method

1. From the initial condition $\mathrm{B} = \mathrm{P} + \delta\mathrm{J}$, extent constants in B.
2. Integrates in $\mathrm{q} = 1, 2 \ldots \mathrm{m}$, as well as so on until confluence happens.
   (a) Split matrixes B among pairs: part 1 this involves all items except one q^{th} columns and rows, as well as part 2, that a q^{th} columns and rows.
   (b) Commutate a remedy for estimated equations $\mathrm{B}_{11}\gamma - \mathrm{P}_{12} + \delta$ LASSO.
   (c) Maximize $\mathrm{b}_{12} = \mathrm{B}_{11}\hat{\delta}$
3. A final phase to obtain $\hat{\vartheta}_{22} = -\hat{\delta}$ among every q, where $\frac{1}{\widehat{\vartheta_{22}}} = \mathrm{b}_{12}{}^{\mathrm{T}}\hat{\delta}$.

3.3 Edge-based neural random forward back propagation (EB-NRBP)

Classification uses an edge-based neural Random back propagation (EB-NRBP) algorithm. It calculates the loss function's gradients. Going down a gradient implies gaining ground toward the curve's base. This process is evaluated in the Equation (4).

$$\omega^{(s+1)} = \omega^{(s)} - \eta \frac{\partial K}{\partial \omega} \quad (4)$$

This is repeated till an optimal solution is found. Modeling and classifying data using a forward gradient algorithm is a classification approach. When the variables of a back-propagation algorithm are set up correctly, it can organize data faster than a model using linear regression. Loss is defined as the deviation from the actual value. The neural classifier uses a forward gradients algorithm, which only uses one instance per cycle, allowing for a rapid solution. After every cycle, the database is arbitrarily mixed, and samples are randomly selected. The formula for the attribute is just the previous value plus the scaling factor are using the Equation (5).

$$\omega_{new} = \omega_{old} + \alpha.\Delta\omega \quad (5)$$

The dimensions of the stage are dependent on the training data. This is done again and over again until an acceptable minimal value is achieved. The generated training set is then tested on a separate database. The approach seeks to delve into a wider range of possibilities and maybe overcome regional minima by introducing randomized disturbances throughout forward gradients. This should enhance the training strategy resilience and generalization. The brain network's training processes are impacted by the unpredictability in the power source frequency upgrades caused by this unpredictability at the border layer. Actual Edge-Based Neuro Randomized technique investigates how the network's capability to find a wider range and efficient depictions of the input data may be improved by controlling randomization in the weighting modifications made throughout retraining.

Effective and yielding the best outcomes for minimal data, forward gradients are a popular method. The slope is meant by gradient here. Forward gradients travel downwards at their most fundamental level to arrive at the curve's minimum point. This is repeated till an optimal solution is found. Proportional gain may be carried out in three distinct ways: the group method, the random method, or the mini-batch method using Equation (6).

$$K_A = \frac{1}{|A|}\sum_{j \epsilon A} K(w_j, z_j) \quad (6)$$

The amount of data used to generate such variations varies with each cycle. Because the meaning of the word random back propagation relies on chance in its operation. Every repetition does not include training on the entire sample but a subset of that dataset. A group is the collection of specimens used in a cycle. To address this issue, the forward gradients algorithm was developed to choose a portion of the sample for every cycle randomly. A typical forward gradient involves classifying data after they have been individually treated to remove influence. But that gets more and more complicated, especially if huge data sets are involved. Modeling and classifying data using forward gradients is an example of racist and discriminatory training. Each cycle of forward gradients uses a single instance, or packet size, instead of several samples. The cost function slope is calculated for a single data point at every cycle. Since modifications are performed just after training individual instances, forward gradients may complete the task more quickly than traditional forward gradients. Whenever the variables of a forward gradient's algorithm are set up correctly, it can classify data faster than a linear regression model. The algorithm for EB-NRBP has been indicated below. EB-NRBP outperforms conventional backpropagation by incorporating Random Forward Gradients and LASSO-based feature selection, achieving faster training, reduced cost function, improved regularization, and higher classification accuracy, making it ideal for real-time, edge-based healthcare applications. Algorithm 2 presented the EB-NRBP.

Algorithm 2. EB-NRBP

1 Initialize weights ω and learning rate η

2 While stopping criteria not met:

3 For each epoch:

4 Randomly shuffle dataset and divide into mini-batches

5 For each mini-batch:

6 Calculate loss function: using Equation (6)

7 Compute gradients $\partial K/\partial \omega$using the chain rule

8 Update weights using Equation (4)

9 Apply forward gradients using Equation (5)

10 Repeat until optimal solution or stopping criteria are achieved

A random data point is chosen from each iteration. More impactful on the algorithm is the learning rate. Learning rates that are initially high are preferable because they cause the algorithm to take significant initial steps before gradually decreasing when the minimal value is approached. The learning rate starts at 0.01.

4. Performance Analysis

The table 3 presents 10-fold cross-validation results for the EB-NRBP model, showing accuracy, precision, recall, and F1-score for each fold. The model demonstrates consistent performance across all folds, with an average accuracy of 98.1%, precision of 97.7%, recall of 97.7%, and F1-score of 97.7%.

4.1 Accuracy

It measures the proportion of correct predictions (both positive and negative) out of the total predictions made. In your study, it reflects the system's overall ability to correctly identify diabetic and non-diabetic cases. High accuracy indicates the EB-NRBP model's reliability, but it doesn't distinguish performance on imbalanced datasets. This table 4 and Figure 3 highlights the accuracy of various models, with the EB-NRBP model achieving the highest accuracy of 98.5%. This demonstrates the superior performance of the proposed approach in accurately diagnosing diabetes compared to other models.

Table 3. 10 Fold Cross Validation Results for EB-NRBP Model

Fold Number	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fold 1	97.5	97.5	97.4	97.4
Fold 2	98.2	97.8	97.9	97.8
Fold 3	98.1	97.6	97.8	97.7
Fold 4	97.9	97.3	97.6	97.5
Fold 5	98.3	97.9	98.0	97.9
Fold 6	98.0	97.7	97.5	97.6
Fold 7	98.4	97.9	97.9	97.9
Fold 8	98.2	98.0	98.1	98.0
Fold 9	97.8	97.5	97.4	97.5
Fold 10	98.1	97.8	97.8	97.8
Average	**98.1**	**97.7**	**97.7**	**97.7**

Table 4. Comparison of Accuracy

Method	Accuracy (%)
ETEODL [20]	97
Random Forest [21]	82.26
Decision Tree [21]	81.02
k-nearest neighbor algorithm [21]	80.55
EB-NRBP [Proposed]	98.5

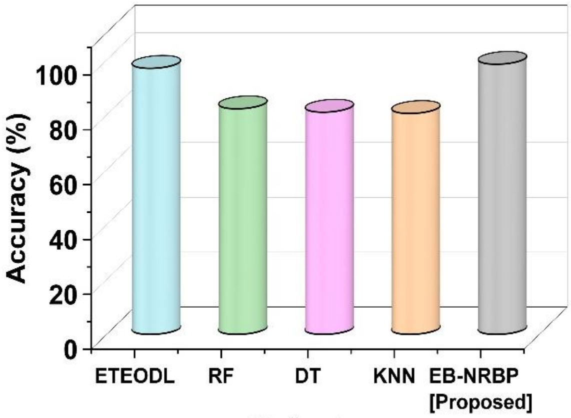

Figure 3. Comparison of Accuracy

4.2 Precision

Specifies the amount of appropriately recognized diabetic cases out of all cases predicted as diabetic. In your study, high precision means fewer false positives, ensuring that most flagged cases truly have diabetes. This reduces unnecessary interventions, enhancing diagnostic reliability and preventing misclassification of healthy individuals as diabetic. Table 5 and Figure 4 shows precision, where EB-NRBP outperforms other models with a precision score of 98.05%. This indicates that the EB-NRBP model excels at minimizing false positives, which is crucial for accurate diabetes diagnosis.

Table 5. Outcomes Precision

Method	**Precision (%)**
ETEODL [20]	97.7
Random Forest [21]	83.47
Decision Tree [21]	83.02
k-nearest neighbor algorithm [21]	81.20
EB-NRBP [Proposed]	98.05

4.3 Recall

Measures the model's ability to correctly detect all actual diabetic cases. It highlights the system's capacity to minimize false negatives. In your study, high recall ensures that most diabetes cases are identified, crucial for early diagnosis and preventing missed cases, thus enhancing patient outcomes. The recall metric in Table 6 and Figure 5 reveals EB-NRBP's ability to correctly identify diabetes cases, with the highest recall of 98.25%. This highlights the model's efficiency in identifying true positives, ensuring fewer missed diagnoses compared to other methods.

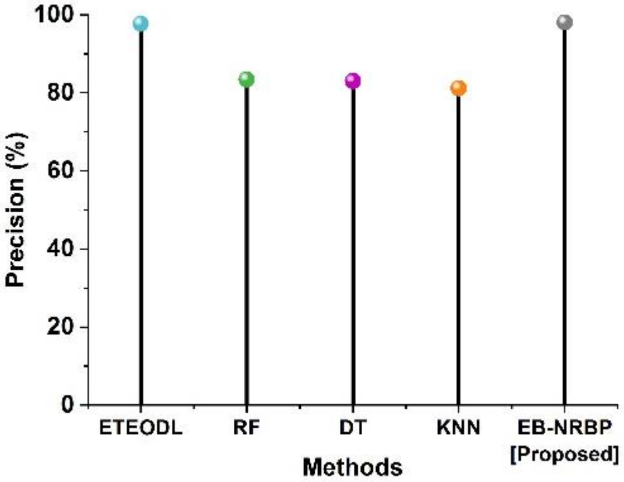

Figure 4. Comparison of precision

Table 6. Outcomes of Recall

Method	Recall (%)
ETEODL [20]	97.7
Random Forest [21]	80.45
Decision Tree [21]	77.98
k-nearest neighbor algorithm [21]	79.50
EB-NRBP [Proposed]	98.25

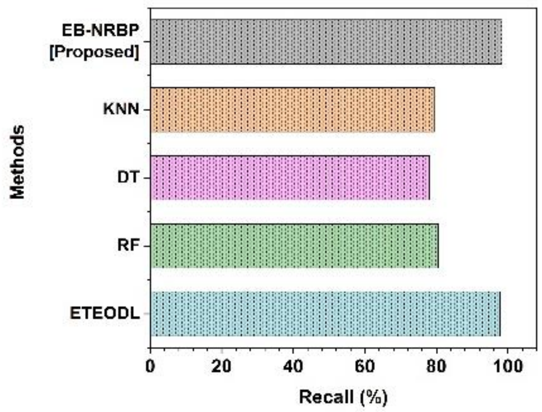

Figure 5. Comparison of Recall

4.4 F1 Score

The harmonic mean of precision and recall, balancing both metrics. It is especially useful for evaluating models on imbalanced datasets. In your study, a high F1 Score indicates that the EB-NRBP model effectively identifies diabetic patients with a good balance between avoiding false positives and false negatives. F1-Score in Table 7 and Figure 6 combines precision and recall, where EB-NRBP again outshines other methods, scoring 98%. This balance of precision and recall ensures the model's robust performance, making it a reliable tool for early diabetes diagnosis in healthcare applications.

Table 7. Comparison of F1-Score

Method	F1-Score (%)
ETEODL [20]	96
Random Forest [21]	82.26
Decision Tree [21]	84.05
k-nearest neighbor algorithm [21]	81.59
EB-NRBP [Proposed]	98

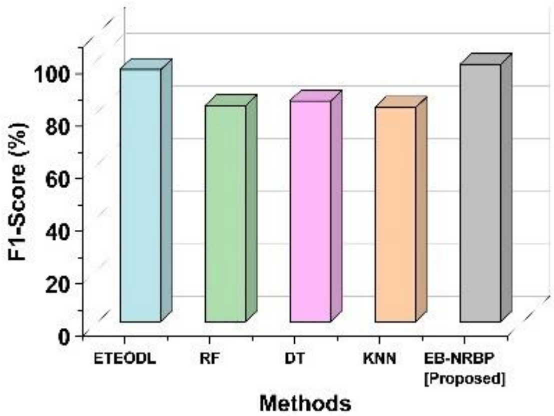

Figure 6. Comparison of F-1 scores

5. Conclusions

Diabetic illness is challenging to diagnose and cure because there aren't enough rules in place to create conditions that encourage appropriate habits, and there isn't excellent medicine available in many places. Treatment for diabetes focuses on regulating blood sugar levels with medication, dietary changes, and physical activity to reduce the risk of complications. Whether this illness isn't correctly identified and treated in a timely way, it may lead to devastating complications and even death. This study presents an idea for an IS based on AI to evaluate the healthcare sector. The proposed system has been applied to the Diabetes Mellitus dataset to assess the model's efficacy. LASSO, a technique for selecting features, has been used in the database. The classification was developed using the EB-NRBP algorithm. With neural random forward gradients, LASSO outperforms other classifiers. Additionally, the AI-based IS's categorization outcomes are contrasted with IoT, ANN, RNN, and IoMT findings. Compared to the different approaches, the EB-NRBP classifier has the highest classification accuracy (98%) of all the above mentioned techniques.

5.1 Limitation and Future scope of the study

Diabetic illness is challenging to diagnose and cure due to insufficient rules, promoting unhealthy habits, and limited access to effective medicine. Timely identification and treatment are crucial to prevent complications. The proposed AI-based system can be applied to various medical datasets for diabetic detection, with future evaluations on high-dimensional samples for model stability and resilience.

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Natesh Mahadev: Conceptualization, Methodology, Validation. Shankar R: Software, Implementation. Sowmya V L: Conceptualization, Investigation, Writing - review & editing. Anitha Premkumar: Writing original draft, Validation. Rajesh Natarajan: Methodology, Validation. N. Thangarasu: Software, Implementation. Shashi Kant Gupta: Methodology, Validation, Writing original draft, Writing -review & editing.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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