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Bridging Horizons in Diabetes Prediction: A Comparative Exploration of Machine Learning and Deep Learning Approaches in Pima Indian Women

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***Abstract*— This study has demonstrated that diabetes prediction models will require powerful machine learning and anomaly detection methodologies in practice. Researchers are exploring novel outlier identification algorithms to enhance predictions. This study has addressed various concerns outlined in prior research. According to this study, diagnostic records, when combined with powerful machine learning such as Adaboost and XGBoost, can offer a precise forecast of the likelihood of diabetes. RNNs also improved deep learning, according to experts. Experts use IQR for the straightened subspace to detect outliers. The stand appears to have a highly positive impact on prediction models. IQR-boosted RNNs outperform XGBoost and AdaBoost in terms of prediction and efficiency. This suggests that combining outlier detection with advanced machine learning could potentially improve diabetes diagnosis and care. The identification of IQR outliers, using RNNs cultivated through iteration with a different line of machine learning, may improve diabetes prediction outcomes. RNN produces better results, with 93% accuracy. The study demonstrated that enhanced machine learning and outlier detection led to improvements in diabetes prediction algorithms.**

Keywords—AdaBoost, XGBoost, Recurrent Neural Networks (RNN) and Interquartile Range (IQR)

I. Introduction

The excessive amount of blood glucose in diabetes mellitus, a chronic metabolic disease, is due to either inadequate insulin synthesis or inadequate utilization. Even the distinct therapies used to control diabetes mellitus during pregnancy are distinct. Since type 1 diabetes is an autoimmune condition characterized by insulin deficiency, patients with this type require insulin. Type 2 diabetes, which is linked to weight and inactivity, is managed with medication and modifiable lifestyle factors. For the duration of your pregnancy, you may be able to regain control of your diabetes with diet and exercise, but you may need medication. Hivert et al. [1] consider the danger of uncontrolled diabetes, which increases the prevalence of disease such as cardiac diseases and renal insufficiency.

II. Literature Survey

Using cutting edge techniques for data gathering and analysis, Saeedi et al. (2019) [2] provide a thorough examination of the prevalence statistics of diabetes both locally and globally. Even if their approach is based on a huge dataset and provides perceptive information that affects global health policy, its limitations are due to the quality of the data and the need for more accurate localized forecasts. This points to a need for more study to enhance regional diabetes prediction algorithms. More research is needed to improve regional diabetes prediction systems. Abbasi et al. (2012) [3] analyse the latest type 2 diabetes risk prediction algorithms and discuss which ones are most realistic.

In their diabetic research, Mujumdar et al. [4] did analysis on big data and combined AdaBoost and Logistic Regression variables to forecast diabetics in advance. This raises the prospect of correctly recognizing diabetes cases that have not yet been diagnosed.

A detailed machine learning diabetes prediction method is published by M. K. Hasan et al. [5]. They aim to meet the requirement for precise early diabetes diagnosis. Their strategy comprises filling data gaps, selecting relevant features, standardizing data, and finding and removing abnormalities. Next, use several machine learning classifiers. The authors use a novel weighted ensemble technique to reward models with better AUC values. Their 0.950 AUC on the Pima Indian Diabetes Dataset shows that their method is superior. Sarwar, Muhammad Azeem, et al. [6] studied predictive analytics in medicine in 2020. This study focused on six machine learning algorithms for diabetes early diagnosis. SVM and KNN algorithms provide medical practitioners with meaningful information with 77% accuracy. However, further study is needed to see if similar findings apply elsewhere. Diabetes has major health consequences, hence Shariff et al. [20] and Soni et al. [7] emphasize early identification and treatment. Their research, which uses many algorithms, shows that early diabetes prediction can improve patient outcomes and healthcare decision-making with 77% classification accuracy. The findings show how machine

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learning improves diabetes treatment and helps clinicians make educated decisions.

Rani et al. predict a global diabetes epidemic by 2035 [8]. They emphasize the condition's persistence and high blood sugar risks. Their study develops a predictive technique using a variety of machine learning algorithms for the early detection of diabetes. The Decision Tree algorithm is notable for achieving an astounding 99% accuracy. This emphasizes how important early detection is for various diseases. By 2040, Zou, Quan, et al. [9] and colleagues also projected a notable increase in diabetes cases by employing neural network, random forest, and decision tree methods. They emphasize the importance of feature selection and early prediction, with random forest showing the highest accuracy. Khanamet al. [10] focus on applying data mining and machine learning methods to the early detection of diabetes, particularly through the use of the Pima Indian Diabetes dataset. Their study shows promising outcomes using Neural Network, Support Vector Machine, and Logistic Regression models; with a neural network, they were able to achieve an accuracy of 88.6%. In conclusion, these studies highlight the need of prompt identification in the management of diabetes and the ability of machine learning in healthcare to predict diabetes at an early stage.

A. Motivation

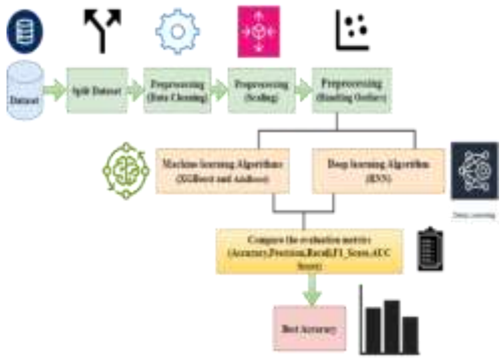
The scientific literature being evaluated is motivated by the urgent global health issue presented by diabetes mellitus. Diabetes is a chronic ailment that is linked to a range of significant health consequences, such as cardiovascular illnesses, renal dysfunctions, include, among other things, visual impairment. The increasing global incidence of diabetes necessitates the prioritization of early identification and efficient treatment in order to mitigate its impact on people and healthcare systems. The motivation for these research stems from the need to use data mining and machine learning methodologies in order to construct precise prediction models. These models may then be utilized to facilitate prompt diagnosis, intervention, and personalized treatment for individuals with diabetes.

B. Research Gap

The dearth of machine learning methods that are both broadly applicable and specifically tailored to the diabetes domain characterizes the current state of research on diabetes prediction. Moreover, there have been scant developments in the creation of novel approaches. The intricacy of diabetes requires specialized models to be addressed, however many studies continue to rely on traditional techniques like logistic regression. Researcher collaboration is necessary to develop accurate and useful models for clinical application.

III. PROPOSED METHODOLOGY

This diabetes prediction research starts with loading the diabetes dataset and preparing it to ensure data quality. To evaluate the model, the dataset is split into training and testing sets. The project has machine learning and deep learning prediction paths. The machine learning section uses Adaboost and XGBoost. Ensemble methods are trained on the training set and tested on the testing set using classification measures like accuracy, precision, recall, F1 score, and AUC-ROC score. We examine preprocessed data with a Recurrent Neural Network (RNN) in deep learning. The model shown in Fig.1 is trained and tested like other machine learning models once the dataset is changed to accommodate Recurrent Neural Networks (RNNs)' sequential structure.



FFig. 1. Research Workflow Diagram

A. Data Collection

The source was the National Institute of Diabetes and Other Digestive and Kidney Diseases diagnostic measurements to predict diabetes. The dataset only accepts Pima Indian females over 21.The number of pregnancies, plasma glucose concentration two hours following an oral glucose tolerance test, diastolic blood pressure, thickness of the skin folds in the triceps, 2-hour serum insulin levels, BMI, function of the diabetes pedigree, age, and a binary variable indicating the presence or absence of diabetes (1 or 0) are the characteristics of each instance. In the predictive modeling challenge, the diagnostic signs are used to forecast diabetes.

Demographic data [11] like age, gender, and heritage helps contextualize the collection. The information is useful for developing and testing predictive models for 21-year-old Pima Indian girls. The dataset's structure and precisely stated target variable enable diabetes prediction using various machine learning and statistical modeling methods. This may help improve medical diagnostics and individualized healthcare for this population.

B. Preprocessing

1) Data Cleaning

Ensuring accuracy in diabetes datasets requires addressing data absences. We begin with a thorough study and assess missing numbers to determine whether they are sporadic or have a major impact. One often used method is imputation, which replaces missing data with computed estimates like means or interpolations. Interpolation and deletion are reasonable choices. Since imputation affects the dataset's consistency, careful consideration is required. Precision is ensured by validation and verification following imputation. A dataset's integrity can be maintained with the use of statistical measures, particularly when handling outliers. Complex data relationships are suitable for regression imputation. In order to guarantee information correctness and integrity—both of which are critical for correctly forecasting diabetes—data cleansing is required. Imputed data are validated using distributions and summary statistics. A dataset's strength is increased when missing data is well managed, which leads to more accurate predictive modeling.

2) Scaling

In order to guarantee appropriate scaling, standardizing diverse factors like blood pressure, BMI, and glucose is essential when producing diabetes datasets. Equitable variable contributions are made possible by methods like Min-Max, Standard, and Robust Scaling, which support machine learning model convergence and efficacy while preserving data integrity and enabling model deployment.

3) *Handling Outliers with Interquartile Range (IQR)*

It is imperative to handle outliers in diabetic datasets in order to guarantee the study's dependability. The Interquartile Range (IQR), which denotes the middle 50% of the data range, is a helpful tool for locating outliers. Conventional techniques like removing or capping outliers ensure that the data is lost-free and of perfect integrity. Validation after treatment is essential for assessing how treatments affect distributions, statistics, and prediction models. This guarantees the practicality and efficacy of the IQR approach in handling diabetic datasets.(shown in Fig.2)

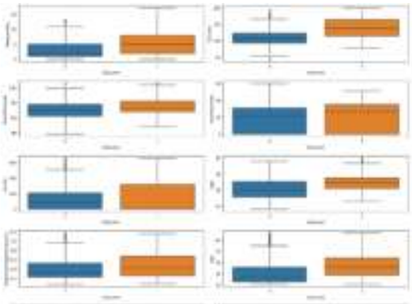


Fig. 2. Before and after removing outliers using IQR

C. Model for Diabetes Prediction

1) *XGBoost*

Xtreme Gradient Boosting, or XGBoost for short, is a powerful machine learning method used for diabetes prediction in predictive modeling. Gradient boosting is a method that builds a powerful model by using weak learners, usually decision trees. This model's primary attributes are its flexibility, resistance to overfitting, use of regularization strategies, and provision of feature importance ratings that are instructive. These characteristics have added to its broad appeal for a variety of uses.

2) *AdaBoost*

AdaBoost[13] is a machine learning method that builds a strong prediction model and improves weak learners' accuracy. Increasing weights with repetition makes poor learners favor incorrectly labeled examples. The ultimate projection depends on weak learners' accuracy and contributions. AdaBoost's adaptability to complex data interactions reduces errors and improves forecasts. AdaBoost [14] combines the outputs of multiple weak learners to generate a powerful ensemble model that generalizes well to new data. AdaBoost[15] reduces overfitting in regression and classification. Due to its performance and adaptability, AdaBoost is useful for ensemble learning.

3) *Recurrent Neural Networks (RNN)*

RNNs and LSTMs enhance sequential processing. LSTMs and stronger gating mechanisms outperform RNNs. Reduced gradient fading improves sequence long-term dependency modelling. LSTM memory cells provide selective data storage and alteration [16]. Cell information flow is controlled by input, forget, and output gates. The forget gate decides whether to keep or erase input gate-directed data in the memory cell. Current generation is controlled by an output gate.

Since it stores complex correlations in sequential input, the LSTM neural network is ideal for long-term context understanding. Its uses include language modelling, machine translation, sentiment analysis, financial time series prediction, and weather forecasting [17]. Many sequential data processing applications benefit from LSTM long-range dependency management [18].

The following important formulae regulate LSTM unit memory cell updating in Recurrent Neural Networks (RNNs).

$$Cell_t = forget_t \odot Cell_{t-1} + input_t \odot \tanh(candidate_t) \quad (1)$$

Where, At time t, $Cell_t$ the updated memory cell state.The gate to ignore output at time t is denoted by $forget_t$.The gate to input to output at time t is denoted by $input_t$.Tangent function hyperbolic is denoted by $tanh$.The candidate value for the new cell state is denoted by $candidate_t$.

Input Gate

$$input_t = \sigma(W_{ii}.X_t + b_{ii} + W_{hi}.H_{t-1} + b_{hi}) \quad (2)$$

Where,

- σ is the sigmoid activation function.
- W_{ii} *and* W_{hi} are the input weights for the input
- gate.
- X_t is the input at time t
- H_{t-1} is the hidden state at time t−1.
- b_{ii} and b_{hi} are the biases.

Forget Gate

$$forget_t = \sigma\left(W_{if}.X_t + b_{if} + W_{hf}.H_{t-1} + b_{hf}\right) \quad (3)$$

Candidate Value

$$Candidate_t = tanh(W_{ic}.X_t + b_{ic} + W_{hc}.H_{t-1} + b_{hc}) \quad (4)$$

Output Gate

$$output_t = \sigma(W_{io}.X_t + b_{io} + W_{ho}.H_{t-1} + b_{ho}) \quad (5)$$

$$H_t = output_t \odot \tanh(Cell_t) \quad (6)$$

Where,

- $output_t$ is the output gate output at time t.
- H_t is the hidden state at time t.
- ⊙ denotes element-wise multiplication.

These formulas explain the information flow in an LSTM unit within an RNN, specifically focusing on the updating of the memory cell and the control of information flow through gates.

IV. Results and Discussions

A. Performance metrics Performance assessments using ML algorithms

1) *IQR with XGBoost*

With an accuracy of 70.8%, precision of 58.1%, and recall of 65.5%, the binary classification model performs well. With an F1 score of 61.5%, this model does a good job of balancing recall and accuracy.With a 76.7% ROC AUC score, it can distinguish between positive and negative events with reasonable accuracy (shown in Table I). Further adjustments can improve its effectiveness based on the particular requirements of the application (shown in Fig.3 and Fig.4).

TABLE I. IQR WITH XGBOOST PERFORMANCE METRICS

IQR with XGBoost Results	
Metrics	***Values***
Accuracy	70.77
Precision	58.06
Recall	65.45
f1_score	61.53
AUC Score	76.65

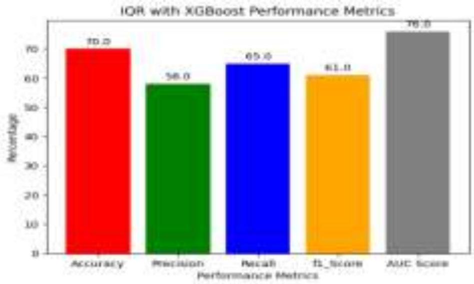


Fig. 3. Bar graph shows IQR with XGBoost performance metrics

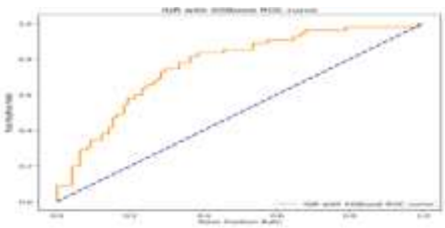


Fig. 4: ROC for IQR with XGBoost performance metrics

2) IQR with AdaBoost

The diabetes prediction model displays robust categorization metrics. With an accuracy of 73.4%, it accurately predicts positive cases at 62.5% and recalls 63.6% of genuine positives. F1 score, at 63.1%, balances accuracy and recall effectively. An ROC AUC value of 78.6% demonstrates its ability to detect positive and negative situations across probability thresholds (shown in Table II). These indicators together show the model's proficiency in diabetes prediction. However, understanding the application environment is crucial for efficient exploitation. Continuous monitoring and refinement are recommended for sustained performance enhancement (shown in Fig.5 and Fig.6).

TABLE II. IQR WITH ADABOOST PERFORMANCE METRICS

IQR with AdaBoost Results	
Metrics	***Values***
Accuracy	73.3
Precision	62.5
Recall	63.6
f1_score	63.0
AUC Score	78.6

Fig. 5. Bar graph for IQR with AdaBoost performance metrics

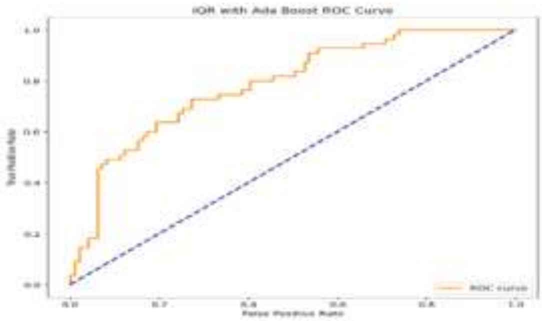


Fig. 6. ROC for IQR with AdaBoost performance metrics

3) Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) usage in deep learning has shown promising results in diabetes prediction with an the Area Under the Curve (AUC) of 0.85, 90.3% accuracy, 88.5% precision, 83.6% recall, and 85.9% F1 score (shown in Table III). These metrics show the diabetes predictor's efficacy by demonstrating its accuracy, precision, and recall balance (shown in Fig.7 and Fig.8).

TABLE III. IQR WITH RNN PERFORMANCE METRICS

IQR with RNN Results	
Metrics	***Values***
Accuracy	90.3
Precision	88.0
Recall	83.6
f1_score	85.9
AUC Score	85.0

Fig. 7. Bar for IQR with RNN performance metrics

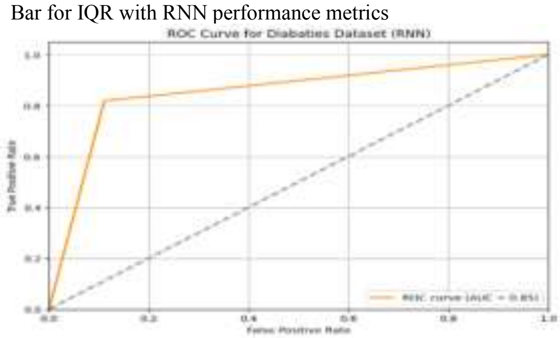


Fig.8. ROC for IQR with RNN performance metrics

4) Comparative performance of IQR outlier detection with XGBoost, AdaBoost and RNN -based diabetes disease prediction

The performance of IQR outlier detection in forecasting diabetes disease using three algorithms—XGBoost, AdaBoost[22], and RNN—is clear. With 70.77% accuracy, XGBoost is reasonable. As seen by its 61.53% F1 score, it balances accuracy and recall. It also has a good AUC of 76.65%. AdaBoost surpasses XGBoost with 73.3% accuracy, 62.5%) precision, and 63.6%) recall, resulting in a 78.6% AUC score (shown in Table IV). Recurrent Neural Networks (RNN) shows the greatest performance improvements due to Interquartile Range (IQR) outlier identification, which boosts accuracy to 90.3%. The RNN achieves an 85.9% F1 score with high accuracy (88.0%) and completeness (83.6%).

TABLE IV. COMPARATIVE ANALYSIS

IQR outlier detection with XGBoost, AdaBoost and RNN Results					
Algorithms	**Accuracy**	**Precision**	**Recall**	**f1_score**	**AUC Score**
XGBoost	70.77	58.06	65.45	61.53	76.65
AdaBoost	73.3	62.5	63.6	63.0	78.6
RNN	90.3	88.0	83.6	85.9	85.0

The RNN's 85.0% AUC shows its better ability to identify positive and negative situations (shown in Fig.9). These findings demonstrate the great value of utilizing RNN-based diabetes prediction models with accurate outlier identification methods like IQR.

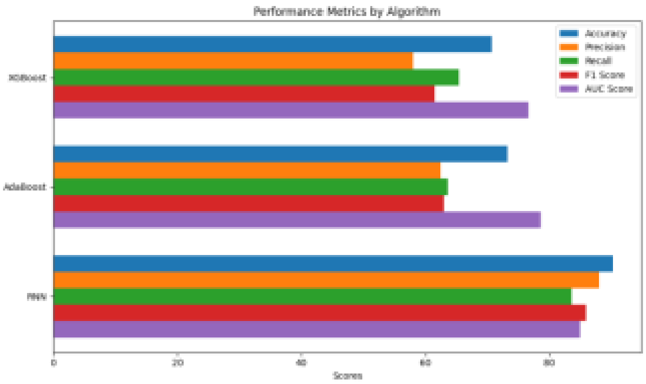


Fig.9. Bar graph for Comparative Performance of XGBoost, AdaBoost, and RNN in Diabetes Prediction performance metrics

V. CONCLUSION

This research illustrates diabetes' complexity, its worldwide public health effect, and the necessity for individualised treatment for its many symptoms. Uncontrolled diabetes requires medication, lifestyle changes, and frequent monitoring to avoid serious health issues. The research emphasises the lack of specialist prediction models and the need for new machine learning methods to effectively identify diabetes risk variables and interactions. Outliers are identified by IQR. Furthermore, diabetes is predicted through Adaboost, XGBoost, and RNN algorithms. The model prediction depended on data cleaning, scaling, and outlier reduction.After removing interquartile range (IQR), it gives AUC by 85.0%, F1 score by 85.9%, and RNN-based prediction accuracy by 90.3%. According to the research, proposed algorithms with removing outliers using IQR increase the accuracy of predictions.

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