Improving Diabetes Forecasting Utilizing Deep Neural Networks and SHAP Interpretability

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***Abstract* — Diabetes is a widespread health issue which is characterized as a chronic metabolic condition in which blood sugar levels are increased beyond a specific threshold. Early and accurate diagnosis can significantly bring down its impediments and for this specific cause our study explores the application of Deep Learning methods and the ways they can be applied so that the prediction is more accurate. Explainable AI (xAI) along with Shapley Additive Explanations (SHAP) is implemented as it will help in increasing transparency in the healthcare systems, Doctors will be able to understand the real root cause from the report and patients will feel more confident after the diagnosis. The dataset used has all the vital health parameters which are necessary for accurate and just diagnosis, The neural network which is developed and trained has shown an accuracy of 88.34% which is better than most of the traditional methods like SVM, Logistic Regression etc. This study aims at simplifying the whole diagnosis and making everyone involved more informed and aware.**

Keywords — Machine Learning; SHAP; XAI; Deep Learning; Neural Networks.

I. INTRODUCTION

Diabetes has been posing as a huge health roadblock for the population, it is a chronic health condition which is epitomized by raised glucose levels. As of now, over 537 million people are affected worldwide and this figure will go up to at least 700 million in the population which already does not have quick access to healthcare that is the impoverished and low-income families hence becoming almost lethal for them. Factors such as urbanization, sedentary lifestyles, poor eating habits, and genetic susceptibility have all played a role in the spiraling epidemic of diabetes, which affects over 77 million individuals in countries like India [2].

Diabetes has immense repercussions on society and the economy. The total cost for both patients and hospital systems is very high due to the management of various vital things which include medication, glucose observation and considerable lifestyle changes. If the diabetes becomes turbulent it then adds a very heavy load on resources due to various impediments like cardiovascular disease and renal failure. Conventional and customary tests which include tests such as blood tests and glucose tolerance tests are still expensive, invasive and not available in many areas, despite that early recognition is very important for avoiding the serious repercussions of this disease. Deep learning which is a part of artificial intelligence (AI) will be of help in the healthcare segment, it has the required ability to improve early diabetes detection. A more tensile and modular way for prediction the risk of diabetes is by the use of models of deep learning [3]. Convoluted and complex can be easily processed through by these deep learning models such as medical history, variables of lifestyle, and physiological measures. They are often labelled as "black boxes" by doctors as they are difficult for them to understand and they don't know anything about its inner workings. Explainable AI (XAI) here comes to rescue, it serves as a mechanism to show how the model comes to its conclusions by provided by XAI through SHAP (Shapley Additive eXplanations), which is different from the conventional deep learning models. With this, models are made ingenuous and trustworthy by showing the contribution of every input in a way doctors can easily understandable. This is of utmost importance as it helps various physicians and doctors to make decisions and advices based on evidences without completely understanding how the technology completely works, XAI's low usage worldwide makes it revolutionary.

Diabetes prediction can be performed by analyzing a patient's glucose parameters, body mass index (BMI), and lifestyle behaviors, XAI helps doctors understand which parameter is more important for deciding the chances of development of Diabetes in a patient. By being this transparent, AI-Operated systems get more trustworthy and health workers are able to work with AI more easily and it blends with the system more rapidly. XAI can also give suggestions and risk management treatments based on the patient's diagnosis. This model improves model's dependability and decreases over-reliance for ill diagnosis of vulnerable patients. XAI's openness and interpretability shows potential increase in healthcare accessibility, leading to early and accurate diagnosis. This provides a fresh perspective that eventually by the help of AI-based diagnostic tools healthcare expenses in late-stage diabetes can be easily reduced and hence making it more affordable. Due to the increasing demand of diabetes treatment worldwide, it is of utmost importance that AI solutions should be more accurate and trustable. XAI can help us in achieving this objective by providing collaboration between technology and healthcare systems.

II. Materials and Methods

The subsections provide indiscriminate details and particular points of interest about the datasets used in this research.

A. Dataset

Framingham Heart Study dataset has been used by this research for predicting Diabetes, a well-established and extensive dataset used in heart health research. This study began in 1948, and has since given remarkable perceptions into the prevention of heart related problems, diabetes and other chronic illnesses. The dataset uses from long-term research including over 5,000 people and has diversified date on physiological, lifestyle, and history of their medical treatments making it an ideal asset for diabetes prediction. Out of the vital elements of the dataset the one which helps the most is the Demographic Information, thus helping in assessment of the Diabetes possibility bank on personal factors. Undeviating physiological touchstone of a person's health and chances of diabetic decline include BMI, blood pressure and blood glucose level along with levels of cholesterol.

The chances of Diabetes (Type 2) accelerate crucially with inconsistent which includes physical activity, smoking and alcohol consumption. These details together with drug use, serves as crucial indication of Diabetes possibility. Each individual's eclectic profile along with clinical (e.g., blood pressure, glucose levels) and behavioral information (e.g., physical activity, smoking) is consolidated in the dataset especially for diabetes prediction. Accurate prediction of Diabetes over time is made possible by the dataset's long-term research specified by data collection at periodic intervals. The Framingham Heart Study dataset guarantees a branched-out representation of elements that affect diabetes prediction due to its extensive scope which incorporates data from over 5,000 humans. These attributes make this dataset an extraordinarily suitable dataset for expansion and assessment of predictive models. As the dataset is easily available in public it allows various scientists and researchers to use it for studies on diabetes and other chronic health related conditions. This dataset uses both lifestyle and physiological parameters to increase the prediction accuracy and reliance, the dataset can be used to create multiple deep learning models designed to forecast diabetes risk.

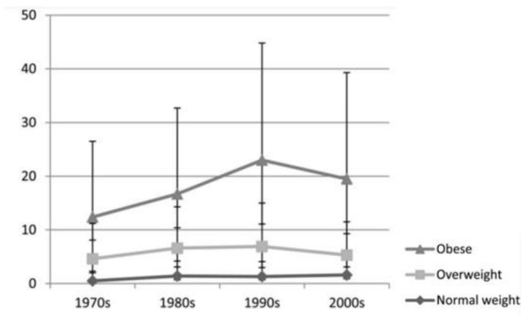

Fig. 1 Occurrence of Diabetes on the basis of BMI Category

TABLE I.
CASES OF DIABETES AND ITS PREVALENCE IN MEN AND WOMEN

Age at the time of Exam	**Men**		**Women**	
	Total	Prevalence (%)	Total	Prevalence (%)
45 to 54	378	5.4	322	3.5
55 to 64	478	9.5	528	7.4
65 to 74	226	12.7	322	11.8
Sum	1082	7.8	1172	6.2

B. Methodology

The major focus in this section is placed on the procedure used to design, create and assess the diabetes prediction model using deep learning along with incorporating XAI.

1) Feature Selection:

The dataset which has been used incorporates 4,240 records and 16 features. This includes demographic details such as age, gender, family history of diabetes, along with lifestyle and physiological data such as BMI, blood pressure and glucose parameters.

2) Data Preprocessing:

Data preprocessing is responsible for developing the dataset for successful model training. Upon completion of the preprocessing stages, the dataset was prepared for training, guaranteeing that the models would be both precise and dependable. Initially, the issue of missing and incomplete data in the dataset is solved by replacing the mean of relevant feature by the use of mean imputation. This made sure that the dataset is complete without any biases. With the use of Standard Scaling, Feature Scaling is applied which in return normalized the data by centering it around the mean of 0 and making the standard deviation of 1. To make sure that the model is not swamped by the size of the characteristics, this was very important for data like glucose parameters and BMI. Less important features are removed by feature selection thus only 14 features were preserved from the native 16 features. Z-score technique was used to spot and remove any outlier that were present to stop them from altering the model's prediction mostly in the case of glucose parameters and BMI. Upon completion of the preprocessing stages, the dataset was prepared for training, guaranteeing that the models would be both precise and dependable.

3) Model Training and Evaluation:

For this study, the selected models are Logistic Regression, Support Vector Machine (SVM), Decision Tree, Random Forest, and Gaussian Naive Bayes. 80% training and 20% testing, with an 80-20 training-test ratio, were approved for the dataset. Principal assessment metric was accuracy. With an accuracy of 88.34 percent higher than that of the other models, the results showed that the Neural Network model outperformed all traditional machine learning approaches including Logistic Regression, SVM, Decision Tree, Random Forest, and Gaussian Naive Bayes. Given the complex character of the diabetes diagnosis challenge and the need for both high sensitivity and specificity, this performance was judged outstanding. A thorough examination was next done using Explainable AI (XAI), especially SHAP (Shapley Additive Explanations), to clarify the decision-making mechanism of the model and so providing predictive transparency and interpretability—critical in clinical decision support. Neural networks efficiently pick up complex, nonlinear patterns from vast and varied data sets, therefore making them especially suitable for tasks like diabetes prediction that require attention to many interdependent elements.

4) Explainable Artificial Intelligence (XAI) using SHAP: The neural network's clarity and interpretability were improved using SHAP (Shapley Additive Explanation). SHAP values help to reveal how each characteristic adds to the model's prediction, therefore offering information on the significance of specific variables in predicting the likelihood of diabetes. Nowhere is this more important than in medical settings, where functional use depends on confidence and understanding of artificial intelligence models. SHAP helps users to assess the judgments of the model and grasp the most important factors affecting risk prediction by quantifying feature importance and showing the effect of every variable. Openness not only enhances the dependability of the model but also encourages its use in real clinical settings, where explanation is vital for the incorporation of AI into normal medical practice.

TABLE II.

PARAMETERS OF DATASET WITH INITIAL VALUES

Parameters of Dataset	Values per Column initially	Missing Values Initially
Male	4240	0
Age	4240	0
CigsPerDay	4211	29
BPMeds	4187	53
prevalentStroke	4240	0
prevalentHyp	4240	0
Diabetes	4240	0
totChol	4190	50
sysBP	4240	0
diaBP	4240	0
BMI	4221	19
Heartrate	4239	1
Glucose	3852	388
TenYearCHD	4240	0

C. Metrics Evaluation

In diabetes detection using deep learning, performance metrics are crucial for evaluating model effectiveness, especially in healthcare applications. Accuracy is a fundamental metric, however, in imbalanced datasets, where one class (e.g., non-diabetic individuals) is more prevalent, accuracy alone may not be sufficient. In these cases, precision and recall provide more valuable insights [6]. Precision measures how accurately the model identifies diabetic cases, focusing on minimizing false positives. Recall, on the other hand, evaluates the model's ability to correctly identify all diabetic cases, emphasizing the importance of minimizing false negatives, which could have severe health consequences [7].

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{1}$$

$$\hat{y}_1, \hat{y}_2, \dots \hat{y}_n \ are\ forcasted\ values$$

$$y_1, y_2, \dots y_n \ are\ distinguished\ values$$

$$n\ is\ the\ number\ of\ distinctions$$

Helping to identify directions for improvement, the confusion matrix offers a thorough representation of the model's forecasts, including true positives, true negatives, false positives, and false negatives [8]. Last, if the model outputs constant forecasts such as the possibility of diabetes, Root Mean Squared Error (RMSE)—generally used for regression models—might be helpful. Low value of RMSE denote better prediction accuracy; it calculates the difference between forecasted and observed values. Taken together, these parameters give a thorough evaluation of model performance, thereby guaranteeing that the system can predict diabetes risk dependably in practical settings

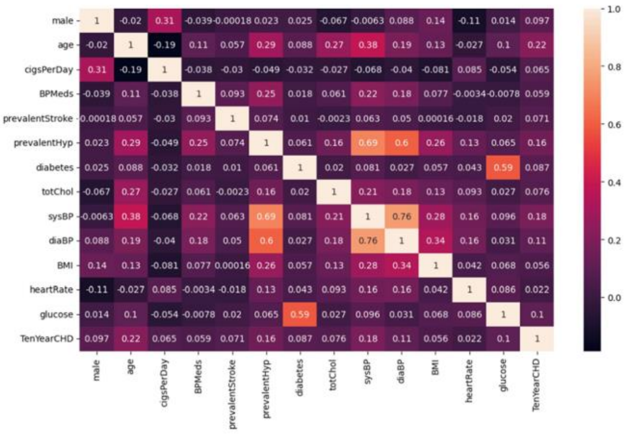

Fig. 2. Confusion Matrix of Framingham Heart Study Dataset

III. RESULTS AND DISCUSSIONS

Using an artificial neural network model and several traditional machine learning approaches, we evaluate their accuracy in spotting diabetes in this analysis. Among the algorithms considered were Random Forest, Decision Trees, Logistic Regression, Support Vector Machine (SVM), and Gaussian Naïve Bayes. None among a number of standard machine learning approaches can equal the performance of neural networks. Though also revealing weaknesses in some respects—for example, an inability to deal sophisticated, non-linear relationships within the data set—we attained 86.15 percent accuracy with the regression model, therefore demonstrating no big concerns. Probably because of overfitting and poor generalizability, Decision Trees were marginally less accurate at 77.94 percent. With an accuracy of 85.50%, random Forest is a set of decision trees. While it falls behind other systems, it can leverage more trees to lower overfitting. With both advantages and drawbacks, SVM scored an 85.95% accuracy [21]. At the very least, issues that SVM is famous for—such as working in high dimensions—may have answers, albeit at the price of resource intensive operation. Consider all properties as independent in the Gaussian Naïve Bayes model, one more straightforward approach with an accuracy of 83.34%. The tests of the Neural Network showed considerable advancement. Each of the models without any optimization had an accuracy of less than 88.34 percent for every algorithm run. This great level of performance is mostly due to the neural network's ability to fit sophisticated and nonlinear models to the data [22]. Traditional algorithms depend on explicit feature engineering or assumptions about the data, but the neural network learns internal structures of the data that are much more complicated hence gains improved performance [23]. This indicates the promise of deep learning techniques, particularly for more difficult classification issues such the diagnosis of diabetes whereby the model's flexibility is an advantage. By training with adaptively changed weights, it exceeds significantly other models. Even with noisy or incomplete data, it has a nice flexibility that will pick the subtle patterns. On the other hand, more classical approaches such as Logistic Regression and Decision Trees call for a lot of preprocessed data and hence are not immune to real-world problems [24]. Furthermore, highlighting their appropriateness for medical uses, where data sets are typically noisy or unbalanced, is this flexibility of neural networks. Secondly, neural networks have scale flexibility—a major benefit. Since a neural network absorbs more data to enhance the prediction, making it future-proof, it will straightforwardly adjust to more features or a larger dataset and as a result potentially even more accurate [25]. Given this, the computational overhead with larger datasets completely buries SVM and the like. Such scalability is a pertinent factor to keep in mind if one is using diabetes detection, as more extensive research and better data might result in richer datasets over time. Neural networks do have difficulties—particularly concerning the computational demands and hyperparameter tuning. Even considering these constraints, the research findings suggest a clear direction for future investigation of architectural optimization and the creation of hybrid models that merge advantages of conventional methods with neural networks.

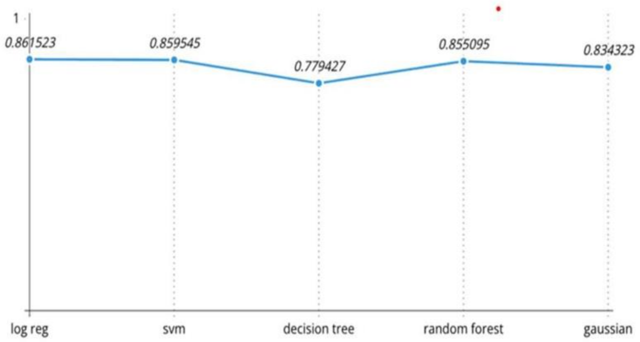

Fig. 3 Finest outcome of every model planned

IV. CONCLUSION

Using sophisticated machine learning algorithms, the diabetes prediction system evaluates vast amounts of medical information and lifestyle elements to establish an individual's risk of developing diabetes. With regard to identifying diabetes risk, the neural network model of the system achieves an astonishing accuracy of 88.34%. This evidence suggests that it is very exact and dependable, therefore it is a good instrument for early detection and treatment. Among other key performance indicators, the system obviously shines at providing valuable information for diabetes prevention considering its high scores in accuracy, precision, and memory. By offering customers instant predictions, the technology empowers them to manage their own health. In this way, they find prospective risks before they arise and so they can make timely lifestyle changes and interventions. Particularly conspicuous is Explainable AI (XAI) (SHAP (SHapley Additive Explanations)) feature using the diabetes prediction system. Including SHAP values lets users view how many factors including age, medical history, blood sugar levels, and lifestyle choices, impacted the predictions of the model and therefore raises openness. This capability is vital in health apps where user acceptance depends on openness and trust. Being able to rationalize the logic of forecasts serves two purposes: it raises user confidence in the system and supports decision making by making clear why the algorithm suggests particular health precautions.

AUTHOR CONTRIBUTION

All the authors have contributed equally in this and have read and agreed to the published version of the manuscript.

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CONFLICT OF INTEREST

The authors have declared no conflict of interest.

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