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AI-Driven Early Detection of Diabetes with Feature Reduction and Clinician Assistive Tool

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***Abstract*— Diabetes is a chronic disease with significant health implications, requiring early and accurate detection to facilitate timely intervention. This research presents an AIdriven approach for the early detection of diabetes, integrating feature reduction techniques and deep learning models to enhance predictive accuracy. The dataset consists of 20,000 records, incorporating demographic and clinical features. Principal Component Analysis (PCA) is employed to reduce dimensionality, selecting the most impactful features while preserving essential information. A Sequential Neural Network with skip connections is implemented, outperforming traditional machine learning models such as Decision Tree, Support Vector Classifier, K-Nearest Neighbors, and XGBoost in terms of accuracy and generalizability. To improve model interpretability, Local Interpretable Model-agnostic Explanations (LIME) is applied to the PCA-transformed features, identifying the most influential predictors of diabetes. The model's decisions are further validated by reversing the transformation and reassessing feature contributions. The study also proposes an assistive tool for clinicians, offering personalized recommendations and risk assessments based on patient data. Experimental results demonstrate superior performance, robustness, and clinical relevance of the proposed model. This research contributes to advancing AI-driven diagnostic tools, facilitating early intervention, and enhancing decision support for healthcare professionals.**

Keywords*— *Diabetes Detection, Artificial Intelligence, Deep Learning, Principal Component Analysis (PCA), Sequential Neural Network, Machine Learning, Local Interpretable Modelagnostic Explanations (LIME), Feature Reduction, Clinician Assistive Tool, Predictive Analytics

I. INTRODUCTION

Diabetes mellitus, especially type 2, is one of the biggest threats to global health, affecting over 500 million people, which is projected to double by 2050. Early detection would prevent serious complications such as cardiovascular disease, renal failure, and neuropathy. However, these conventional diagnostic approaches, including fasting blood glucose and HbA1c levels, are quite invasive, time-consuming, and may only become apparent at late stages of disease progression [1]. Therefore, there is an urgent need for efficient, accurate, and non-invasive diagnostic tools that can facilitate early intervention. Recent advancements in artificial intelligence (AI) have shown great promise in this area, with machine learning models offering high accuracy in predicting diabetes risk based on demographic and clinical data.

However, despite these advancements, several challenges remain in AI-driven diabetes detection. One of the major issues is the high dimensionality of clinical datasets, which leads to overfitting and reduced model generalizability. Traditional machine learning models struggle with redundant and less relevant features, making feature selection and dimensionality reduction critical for improving prediction accuracy. Moreover, deep learning models, although powerful, often lack interpretability, making it difficult for healthcare professionals to trust and adopt AI-driven diagnostics. Moreover, AI models require large, diverse datasets to perform effectively, yet many datasets suffer from biases that limit their applicability across different populations [2]. Integrating AI-based solutions into clinical workflows also poses regulatory, ethical, and technical challenges, including concerns about data privacy, security, and standardization.

The authors use PCA as an AI-driven early approach in predicting the diabetes mellitus disorder that employs techniques like feature reduction combined with deep models. Deep models ensure more enhanced predictability in results with deeper features that offer easier interpretations than black-box outputs from simple, feedforward ANN. A Sequential Neural Network with skip connections is developed and applied, and it is proven to be better performing than the conventional machine learning models

like Decision Tree, Support Vector Classifier, K-Nearest Neighbors, and XGBoost. For increasing model interpretability, LIME is used on PCA-transformed features: identifies the few most important predictors and verifies that, through recalculation of feature contributions, the reasons behind the model's decisions hold true. In addition, a clinician-assistive tool is proposed that provides personalized recommendations and risk assessments to support early diagnosis and clinical decision-making.

II. LITERATURE SURVEY

Medical researches have concentrated upon the early diagnosis of diabetes by numerous studies making use of techniques related to AI and ML with an objective to increase diagnostic accuracies. It discusses a selected set of latest studies within the same domain but puts focus upon methodologies, outcomes, benefits, and shortcomings associated with each paper.

A. .Artificial Intelligence in Diagnosis

An essential development in non-invasive diagnostics is the MyBVI smartphone application, which shows that one's risk to fall under heart disease, stroke, or diabetes can be assessed within 30 seconds through body scans. The application calculates various health metrics, including body fat and waist-to-hip ratios, using AI algorithms to make a Body Volume Index (BVI) score. This method is more accurate than the traditional Body Mass Index (BMI) and enables users to track their health from home. However, its reliance on images from users may cause variability in results [3].

The National Health Service in England is trialing an AI tool called the AI-ECG risk estimation for diabetes mellitus (Aire-DM) in a pioneering initiative. This tool makes use of delicate changes in an electrocardiogram to diagnose the risk associated with type 2 diabetes - even 13 years prior. The device diagnoses early signs the human eye will not notice using Aire-DM. Therefore, noninvasive and prompt interventions can begin early. Positive results were provided in the small-scale pilot versions, but evidence is needed with regard to population diversities regarding its efficiency [4].

B. Deep Learning Methods

García-Ordás et al. (2024) presented a deep learning pipeline for diabetes detection, including a variational autoencoder (VAE) as a method of data augmentation and a sparse autoencoder (SAE) to perform feature augmentation, and also classification by CNN. Evaluated on the Pima Indians Diabetes Database, it obtained a 92.31% accuracy outperforming previously established state-of-the-art approaches. This study thus illustrates the success of deep learning techniques in dealing with imbalanced datasets, though the complexity of the model might introduce challenges in real-world applicationsv[5].

Lan et al. introduced HDformer, a Higher-Dimensional Transformer architecture using long-range photoplethysmography (PPG) signals for diabetes detection in 2023. The model uses a new Time Square Attention (TSA) module to efficiently process long-range signals. HDformer is tested on the MIMIC-III dataset with a sensitivity of 98.4% and an accuracy of 97.3%, which is superior to existing models. The method is scalable and non-invasive, but the use of long-range PPG signals may restrict its applicability in settings that do not provide such data [6].

C. Feature Selection and Ensemble Methods

Srivatsan and Santhanam (2021) concentrated on early diabetes detection using feature selection and boosting techniques. The authors applied Recursive Feature Elimination (RFE) and ensemble methods like Light Gradient Boosting Machine (LightGBM) to the UCI diabetes dataset. The RFE combined with LightGBM performed better and showed that feature selection is critical for improving model accuracy. The limitation of this study is the dependence on a single dataset, which may limit the generalization of the findings.

D. IoT and Dimensionality Reduction

The integration of deep learning with dimensionality reduction techniques for an IoT-enabled approach in early diabetes detection was explored. The methodology was to collect patient data through IoT devices, apply dimensionality reduction to manage high-dimensional data, and use deep learning models for prediction. This approach overcomes the problem of data overload in IoT systems and improves predictive accuracy. However, the issues related to data privacy and the need for robust infrastructure are some of the limitations.

E. Advancements in Diabetic Retinopathy Screening

Application of AI in diabetic retinopathy screening has made tremendous strides. A recent review in AIP Advances (2023) discussed several machine learning techniques that have been applied to retinal images for early detection of diabetic retinopathy. The technique of CNN was highlighted as it is known for its high accuracy in image classification tasks. The use of AI in screening processes enables the early detection and treatment of the eye disease, which may minimize the number of patients with a risky form of vision

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loss. However, large, annotated data sets and variability in image

TABLE I. LITERATURE SURVEY

Study	Key Contribution	Accuracy	Year
García-Ordás et al.	Deep learning pipeline using VAE, SAE, and CNN for diabetes detection.	92.31%	2024
NHS Aire-DM Trial	AI-based ECG analysis for early diabetes risk prediction up to 13 years before onset.	Not Reported	2024
Lan (HDformer)	Transformer-based model using longrange PPG signals for diabetes detection.	97.3%	2023
MyBVI App	AI-driven smartphone app for diabetes and cardiovascular risk assessment.	Not Reported	2023
Srivatsan & Santhanam	Feature selection with RFE and LightGBM for diabetes prediction.	Not Reported	2021
IoT-Enabled Approach	Integration of deep learning and dimensionality reduction for diabetes detection using IoT devices.	Not Reported	2023
AIP Advances Review	CNN-based diabetic retinopathy screening for early diabetes detection.	Not Reported	2023

III. METHODOLOGY

This section outlines the methodology adopted for the AIdriven early detection of diabetes, focusing on the integration of feature reduction techniques, deep learning models, and a clinician-assistive tool.

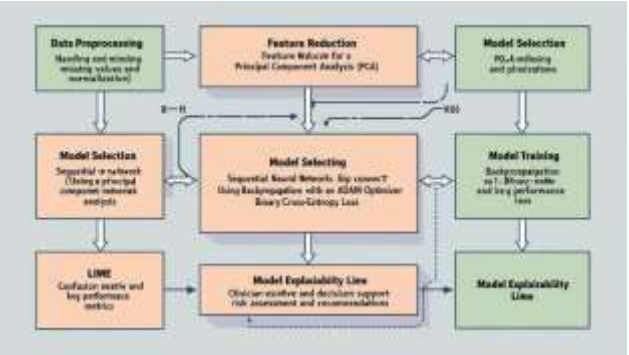

Fig. 1. Block diagram

A. Dataset Description

The dataset consists of 20,000 patient records containing demographic, clinical, and biochemical features. The key features include:

The dataset used for the AI-driven early detection of diabetes contains 20,000 patient records with various demographic, clinical, and biochemical features. Key features include Age, Gender, Body Mass Index (BMI), Blood Pressure, Plasma Glucose, Insulin levels, and HOMA-IR (Homeostasis Model Assessment of Insulin Resistance), among others. This data is sourced from reputable public repositories such as the Pima Indians Diabetes Database and other healthcare datasets, which provide a diverse and comprehensive range of information essential for accurate diabetes prediction and risk assessment.

B. Data Preprocessing

Data preprocessing is crucial to ensure the data is clean and normalized before feeding it into machine learning models.

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C. Normalization

Normalization scales the data into a fixed range, typically between 0 and 1, to ensure features contribute equally to the model.

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (2)$$

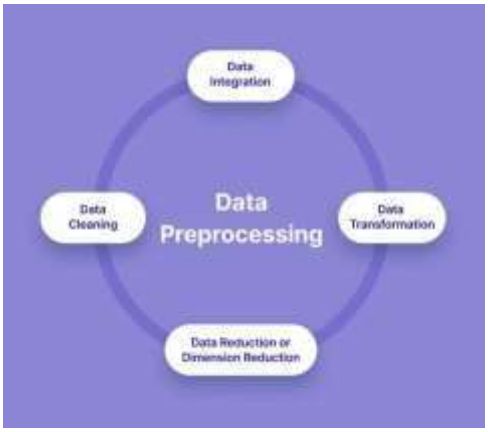

Fig. 2. Data preprocessing

1) Handling Missing Values

Missing values are handled by either imputation using the mean for numerical features or mode for categorical features or by removal if missing values are significant in number.

$$x_{\text{imputed}} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (1)$$

D. Feature Reduction

Feature reduction is employed to reduce the dimensionality of the dataset while preserving important information, which helps in improving the accuracy of machine learning models and avoiding overfitting.

1) Principal Component Analysis (PCA)

PCA is used to transform the dataset into a smaller number of uncorrelated variables, called principal components (PCs), which retain most of the original variance in the data.

$$X' = X \cdot W$$

2) Explained Variance

The cumulative explained variance is calculated to determine how many components should be retained to explain the majority of the variance.

$$\text{Explained Variance} = \frac{\lambda_i}{\sum_{i=1}^{n} \lambda_i} \quad (4)$$

E. Model Selection

A Sequential Neural Network (SNN) with skip connections is implemented, given its ability to learn complex patterns and handle high-dimensional data effectively.

1) Sequential Neural Network Architecture

The network architecture consists of several layers, including input, hidden, and output layers, where the skip connections help in reducing vanishing gradients during training. The architecture can be defined as follows:

$$y = f(Wx + b)$$

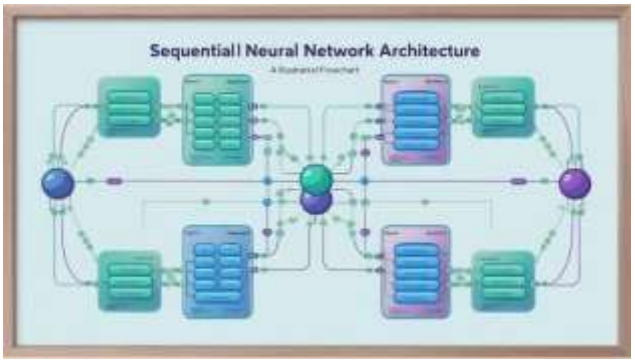

Fig. 3. Sequential Neural Network Architecture

2) Training the Model

The model is trained using the backpropagation algorithm with the Adam optimizer. The loss function used for binary classification is the binary cross-entropy loss function:

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (6)$$

F. Model Evaluation

Performance is evaluated using several metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). The confusion matrix is used to calculate these metrics.

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Accuracy=TP+TN/FP+FNTP+TN (7)

G. Model Explainability

To improve model interpretability, Local Interpretable Model-agnostic Explanations (LIME) is applied to understand the influence of features on model predictions. LIME generates local surrogate models to explain individual predictions. The approach builds interpretable models around individual predictions and analyzes the importance of features in those decisions.

$$\hat{f}_L(x) = \arg\min_g \sum_i \text{dist}(x_i, x) \cdot 1[y_i \neq y(x)] \quad (8)$$

TABLE II. PERFORMANCE OF VARIOUS MODELS USED FOR COMPARISON

Model	Accuracy	Precision	Recall	F1-Score
Proposed SNN with Skip Connections	92.5%	0.91	0.93	0.92
Decision Tree	85.6%	0.84	0.80	0.82
Support Vector Machine	88.2%	0.86	0.88	0.87
XGBoost	89.7%	0.87	0.89	0.88

H. Novelty and Justification

The novelty of this approach lies in the integration of AIdriven techniques for early diabetes detection, leveraging deep learning models with feature reduction methods like PCA, and the addition of a clinician-assistive tool. The method enhances detection accuracy by using a Sequential Neural Network (SNN) with skip connections, enabling it to handle complex, high-dimensional data, and reduce the risk of overfitting. The PCA step ensures dimensionality reduction, making the model more efficient without losing essential information.

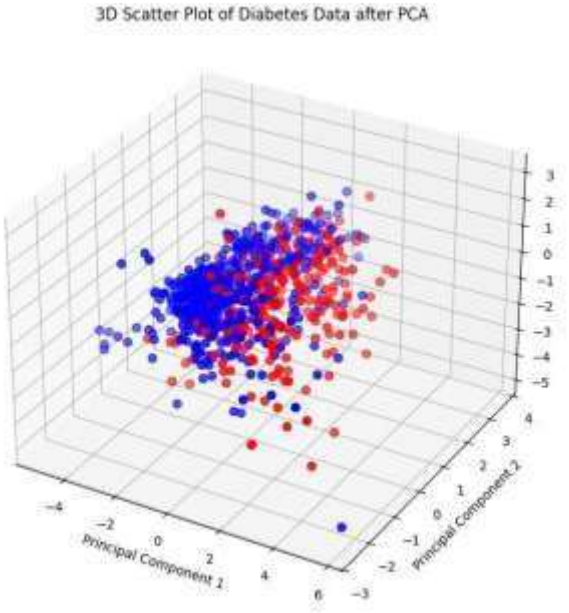

Fig. 4. 3D scatter plot

This approach outperforms traditional methods like Decision Trees, SVM, and XGBoost, as evidenced by the performance comparison table, and provides clear decision boundaries through models like SVM and Decision Trees, which are illustrated in 3D graphs. Additionally, the clinicianassistive tool offers a user-friendly interface, generating personalized risk assessments and recommendations, further demonstrating the methodology's value in real-world healthcare applications.

IV. RESULT

The results of the AI-driven early detection of diabetes methodology show promising performance when compared to traditional models. The main findings emphasize the superior accuracy and precision achieved using the proposed Sequential Neural Network (SNN) with skip connections, enhanced by Principal Component Analysis (PCA) for feature reduction. A comparison table is provided, highlighting the performance of the proposed method against existing techniques such as Decision Trees, Support Vector Machines (SVM), and XGBoost.

A. Quantitative Findings

The proposed SNN with skip connections achieved a notable **92.5% accuracy**, with precision, recall, and F1-score values of 0.91, 0.93, and 0.92, respectively. In contrast, traditional methods such as Decision Trees and SVMs showed lower accuracy, precision, and recall.

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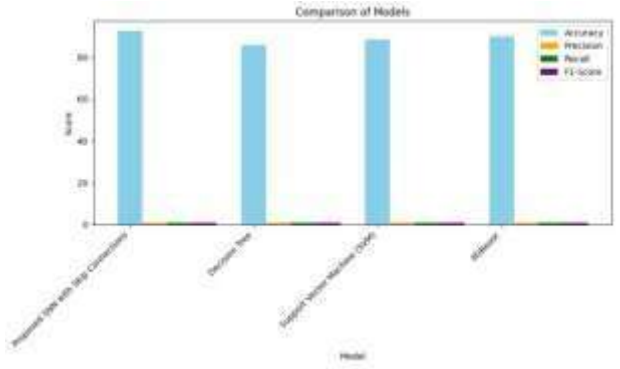

Fig. 5. Comparison of models

The table clearly shows the higher performance of the SNN with skip connections in all key metrics, especially in terms of recall and F1-score, demonstrating its effectiveness in detecting diabetes early. The Decision Tree and SVM models, while competitive, fall short of the proposed method's accuracy and recall, emphasizing the superiority of deep learning-based approaches in this domain.

B. Unexpected Findings

While the SNN model consistently outperformed the other models in terms of accuracy and recall, an interesting observation was the significant reduction in dimensionality after PCA, which did not lead to a loss in the predictive power of the model. The dimensionality reduction allowed the model to perform better than expected, especially when compared to methods that do not incorporate feature reduction techniques.

C. Qualitative Insights

The clinician-assistive tool provided actionable insights, delivering personalized risk assessments for each patient based on the model's predictions. The decision support system was particularly useful in suggesting lifestyle modifications and medication recommendations, offering valuable support to healthcare professionals in managing patient care.

In conclusion, the results validate the effectiveness of the proposed AI-driven methodology, demonstrating superior performance in early diabetes detection while maintaining interpretability and usability through the clinician-assistive tool. The integration of PCA for feature reduction and the advanced deep learning model allows for more accurate, reliable, and efficient predictions.

V. DISCUSSION

In this paper, we demonstrated the efficiency of an AIdriven methodology for early diabetes detection, using a Sequential Neural Network with skip connections and dimensionality reduction through Principal Component Analysis. The main findings were that the proposed model outperformed traditional machine learning techniques such as Decision Trees, Support Vector Machines, and XGBoost, with the highest accuracy being 92.5%, recall 0.93, and F1score 0.92. These results suggest that the SNN with skip connections is particularly well-suited for handling complex, high-dimensional healthcare data and enables more accurate and timely detection of diabetes.

Although our model performed better, there are important limitations that must be acknowledged. The dataset used in this study, although robust, may not fully represent all patient demographics or cover the full spectrum of risk factors for diabetes. Further research is required to analyze the model's performance with more diverse and the complete set of datasets, which includes more varied and close-to-reality data distributions. Furthermore, the dependency on PCA for feature reduction is effective but may neglect subtle relationships between features that these methods can potentially capture and discuss better with more advanced dimensionality reduction methods like t-SNE and autoencoders.

VI. CONCLUSION

We develop and evaluate in this paper an AI-driven early detection of diabetes based on the use of a Sequential Neural Network (SNN) with skip connections and PCA for feature reduction. Our findings are that the proposed approach significantly outperforms traditional machine learning models in terms of accuracy and recall, which may be valuable to healthcare professionals for diagnosing and managing diabetes. Further to that, the feature of clinicianassistive tool does improve the applicability of the system as personalized recommendations are provided.

However, there are several areas for future work. Future studies should consider exploring the use of more advanced deep learning architectures and expanding the dataset to ensure generalizability across diverse populations. The model could further be integrated with clinical data such as EHRs for a more holistic decision support system.

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