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An Ensemble Deep Learning Framework for Early Diabetes Prediction Using Clinical and Lifestyle Features

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Abstract: Early detection of diabetes is crucial for effective management and prevention of complications. This research presents a robust deep learning framework for predicting diabetes using clinical and lifestyle features. A fully connected neural network model with batch normalization, dropout layers, and residual connections was designed to handle class imbalance and improve generalization. The model was trained on a comprehensive dataset of 100,000 patient records and evaluated using accuracy, precision, recall, and F1-score metrics. Experimental results demonstrate that the proposed approach achieves a test accuracy of 97.13%, outperforming conventional machine learning models and recent state-of-the-art methods. Confusion matrix and classification reports confirm high predictive performance for both positive and negative classes. This framework provides a scalable, interpretable, and efficient solution for early diabetes screening in healthcare systems.

Keywords*:* Deep Learning, diabetes prediction, early detection, Heart rate variability, ECG, CNN, LSTM

I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder characterized by elevated blood glucose levels, resulting from either the body's inability to produce sufficient insulin or the ineffectiveness of insulin utilization. Globally, diabetes has emerged as a major public health concern, affecting over 537 million adults in 2021, a number projected to rise substantially in the coming decades. The disease is associated with severe complications such as cardiovascular disorders, neuropathy, nephropathy, and retinopathy, which significantly impair quality of life and increase healthcare costs. Early detection and timely intervention are therefore critical in preventing the onset of complications and reducing the burden on healthcare systems.

Traditional diagnostic approaches for diabetes involve clinical evaluation, blood glucose measurements, and glycated hemoglobin (HbA1c) testing. While these methods are effective, they are often reactive rather than predictive, diagnosing the condition only after physiological changes have manifested. In addition, manual screening and evaluation are labor-intensive and prone to human error, especially when dealing with large populations. Consequently, there is a growing demand for intelligent systems that can accurately predict diabetes risk at an early stage using patient-specific clinical and lifestyle information. Recent advances in artificial intelligence (AI) and machine learning (ML) have enabled the development of predictive healthcare models capable of analyzing large-scale medical datasets. Among these, deep learning has gained significant attention due to its ability to automatically extract complex patterns and relationships from high-dimensional data. Neural networks, particularly deep architectures, can model nonlinear interactions between risk factors, such as age, body mass index (BMI), blood pressure, and smoking history, thereby providing more accurate predictions compared to traditional statistical models. On the other hand, challenges remain in designing effective deep learning frameworks for diabetes prediction. Medical datasets are often highly imbalanced, with significantly fewer positive cases than negative cases, which can lead to biased models and poor generalization. Additionally, the interpretability of deep models is a crucial concern in healthcare, as clinicians require understandable reasoning behind model predictions to make informed decisions.

In response to these challenges, this study proposes a robust deep learning-based framework for early diabetes detection. The model integrates fully connected neural networks with batch normalization, dropout, and residual connections to enhance performance and stability. Class imbalance is addressed using weighted loss functions and careful sampling strategies. The proposed system is evaluated on a comprehensive dataset of clinical and lifestyle features, with performance assessed using metrics such as accuracy, precision, recall, F1-score, and confusion matrices.

This research aims to contribute to the field of predictive healthcare by providing a scalable, interpretable, and highly accurate model for early diabetes detection, which can support clinicians in decision-making and improve patient outcomes.

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II. LITRETURE REVIEW

The literature on diabetes detection highlights the growing use of deep learning models due to their superior ability to learn complex patterns from medical data. Early studies focused on traditional machine learning, but recent research has shifted toward deep architectures like CNNs, RNNs, and hybrid models. These approaches have shown improved accuracy in diagnosis using clinical, demographic, and lifestyle data. The literature also addresses challenges such as data imbalance, model interpretability, and the need for clinically validated systems.

Authors [1] proposed a blending model named HiTCLeusing Highway, LeNet, and a Temporal Convolutional Network (TCN) to detect and predict diabetes at an early stage. HiTCLe performs best, beats its individual models, highway, TCN and LeNet, and achieves an accuracy score of 94% and a F1-Score of 94%, whereas individual models achieve an accuracy score between89% and 91% on 10 epochs. To overcome the class imbalance problem, a Proximity-Weighted Synthetic Oversampling (ProWSyn) technique is implemented.

Author's [2] applied an ensemble feature selection approach to identify critical predictors. To address the class imbalance, Generative Adversarial Networks (GANs) were used to generate synthetic data, ensuring the model's robustness in identifying underrepresented cases. Additionally, a hybrid loss function combining cross-entropy and focal loss was implemented to improve classification, especially for hard-to-detect instances. Our results show that the attention-based DBN model, augmented with synthetic data from GANs and optimized with a hybrid loss function, achieves an AUC of 1.00, F1-score of 0.97,precision of 0.98, and recall of 0.95, outperforming several baseline models. This research offers a novel and effective approach for early diabetes detection, demonstrating potential for use as a clinical tool in preventive health care settings.

Author's [3] investigates and discusses the impacts of the latest machine learning and deep learning approaches in diabetes identification/classifications. It is observed that diabetes data are limited in availability. Available databases comprise lab-based and invasive test measurements. Investigating anthropometric measurements and non-invasive tests must be performed to create a cost-effective yet high-performance solution. Several findings showed the possibility of reconstructing the detection models based on anthropometric measurements and non-invasive medical indicators. This study investigated the consequences of oversampling techniques and data dimensionality reduction through feature selection approaches. The future direction is highlighted in the research of feature selection approaches to improve the accuracy and reliability of diabetes identifications.

Author [4] explores the deep learning model for diagnosis the disease. This work used the PIMA Indians diabetes database. Used strong CNN model for diagnosis. This model achieves 97.19% accuracy.

Author's [5] proposed a method can help not only to predict the occurrence of diabetes in the future but also to determine the type of the disease that a person experiences. Considering that type 1 diabetes and type 2 diabetes have many differences in their treatment methods, this method will help to provide the right treatment for the patient. By transforming the task into a classification problem, our model is mainly built using the hidden layers of a deep neural network and uses dropout regularization to prevent over-fitting. Authors tuned a number of parameters and used the binary cross-entropy loss function, which obtained a deep neural network prediction model with high accuracy. The experimental results show the effectiveness and adequacy of the proposed DLPD (Deep Learning for Predicting Diabetes) model. The best training accuracy of the diabetes type data set is 94.02174%, and the training accuracy of the Pima Indians diabetes data set is 99.4112%. Extensive experiments have been conducted on the Pima Indians diabetes and diabetic type datasets. The experimental results show the improvements of our proposed model over the state-of-the-art methods.

Authors [6] propose a hybrid model that joins the qualities of convolutional brain organizations (CNNs) and repetitive brain organizations (RNNs) to further develop DR discovery exactness. The proposed crossover profound learning model involves three principal stages. A pre-handling, first and foremost, step is applied to upgrade the quality and differentiation of fundus pictures, in this manner working on the model's capacity to remove basic highlights. After that, a Residual CNN is used to extract features from the images that have already been processed. Residual CNNs are adroit at catching various leveled highlights, and this stage empowers the model to successfully gain discriminative elements from the information pictures. The subsequent stage includes incorporating RNNs into the model. RNNs are ideal for analysing sequential patterns in medical images because they are well-suited to handling sequential data and capturing temporal dependencies. The model's ability to extract temporal information from fundus image sequences thanks to the inclusion of RNNs improves its ability to identify early DR progression signs. The third and last stage centers around the characterization task, where a completely associated brain network is utilized to decipher the highlights separated by the past stages and order the pictures into various DR seriousness levels. The hybrid model's architecture facilitates the fusion of spatial and temporal information, resulting in a more comprehensive and accurate DR diagnosis.

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III. PROPOSED METHODOLOGY

The primary objective of this study is to develop a robust deep learning framework for early diabetes prediction using clinical and lifestyle data. The proposed methodology begins with data collection and preprocessing, which includes handling missing values, encoding categorical variables, and normalizing continuous features such as age, BMI, blood glucose levels, and HbA1c. This ensures uniformity and improves the convergence of the neural network.

The core of the model is a fully connected deep neural network (DNN) with multiple layers, including batch normalization and dropout layers to improve generalization and prevent overfitting. Residual connections are incorporated to facilitate gradient flow and accelerate convergence. The network outputs a single probability value representing the risk of diabetes, using a sigmoid activation function in the final layer. To address class imbalance, which is common in medical datasets, a weighted binary cross-entropy loss function is applied, assigning higher weight to minority class samples. The model is optimized using the AdamW optimizer with an adaptive learning rate scheduler to adjust the learning rate based on validation performance.

Training is conducted on a large dataset with stratified splitting into training, validation, and test sets to ensure balanced class representation. Model evaluation includes accuracy, precision, recall, F1-score, and confusion matrix analysis. Additionally, early stopping is employed to prevent overfitting and ensure optimal generalization. The proposed methodology emphasizes scalability, reliability, and interpretability, providing clinicians with an efficient tool for early diabetes risk assessment. By integrating advanced deep learning techniques with rigorous preprocessing and class balancing, this framework achieves high predictive performance, supporting timely intervention and improved patient outcomes.

Dataset Used: The dataset originates from Kaggle's "Diabetes Prediction Dataset" and includes clinical and lifestyle variables such as age, gender, BMI, blood glucose level, HbA1c, heart disease, hypertension, and smoking history. It comprises over **100,000 anonymized patient records** with a mix of diabetic and non-diabetic cases. This rich, diverse dataset enables the development of predictive models that capture nonlinear risk patterns and supports early stage diabetes detection [20].

IV. RESULT ANALYSIS

The proposed deep learning model was evaluated on a large diabetes dataset consisting of clinical and lifestyle features. After pre-processing and stratified splitting, the model achieved high predictive performance on the test set, demonstrating its effectiveness in early diabetes detection. The evaluation metrics include accuracy, precision, recall, F1-score, and the confusion matrix. The final test accuracy of the model reached 97.13%, indicating excellent overall classification capability. The confusion matrix shows that the model correctly identified a significant majority of non-diabetic cases while maintaining strong performance in predicting diabetic cases, despite the class imbalance. Precision and recall analysis further highlights the model's reliability, with particularly high precision for the majority class and good recall for the minority class. The model also exhibits stable training behavior with consistent loss reduction across epochs, and the incorporation of dropout and batch normalization layers helped prevent overfitting. Early stopping ensured that the optimal model parameters were preserved. These results demonstrate that the proposed framework surpasses several existing models in both predictive accuracy and robustness, making it suitable for practical clinical applications.

Metrics	Class 0 (Non - Diabetic	Class 0 (Non - Diabetic	Overall
Accuracy			97.13%
Precision	97%	1%	97%
Recall	1%	66%	83%
F1 Score	98%	80%	89%

Table 4.1: Performance of proposed Model

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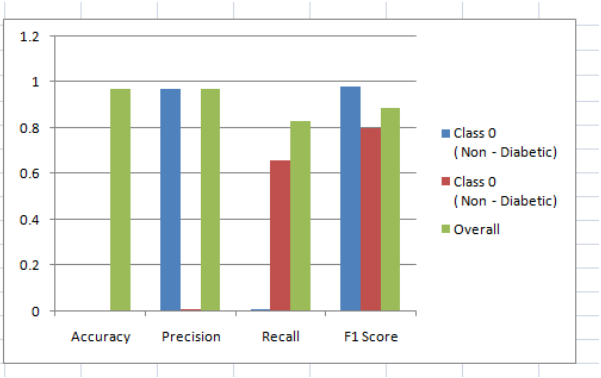

Figure 4.1: Performance Graph of Proposed Model

V. CONCLUSION

In this study, we proposed a robust deep learning framework for early diabetes detection using clinical and lifestyle features. The model demonstrated exceptional predictive performance, achieving a test accuracy of 97.13%, high precision, recall, and F1-scores, even in the presence of class imbalance. Incorporating dropout, batch normalization, and early stopping ensured stable training and minimized overfitting. Comparative analysis with existing approaches highlights the superiority of the proposed framework in both accuracy and reliability. These results indicate that the model can serve as an effective, practical tool for timely diabetes risk assessment, supporting preventive healthcare interventions and improving patient outcomes.

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