Non-Invasive Diabetes Risk Assessment Model Using Deep Learning

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Abstract- *This Current diabetes detection methods predominantly rely on invasive blood tests, posing significant barriers to widespread, proactive screening. This paper proposes the development of a highly precise and accurate non-invasive predictive model for assessing diabetes risk. Leveraging a comprehensive set of readily observable symptoms, anthropometric measurements, lifestyle habits, and medical history, this Deep Learning/Neural Network model aims to identify individuals at risk without requiring blood samples. Experimental results demonstrate the model's effective learning, convergence, and strong predictive capabilities, with key features like genetic risk and physical activity significantly influencing the predictions. The insights gained from this research also highlight crucial non-invasive pathways for diabetes prevention and reduction. The proposed solution seeks to serve as an accessible initial screening tool, a proactive awareness generator, and a valuable resource for public health initiatives, ultimately reducing the burden of diabetes and its associated complications through early detection and timely intervention.*

I. INTRODUCTION

Diabetes mellitus has emerged as a global health crisis, with its prevalence steadily increasing across all income levels. The disease, if undiagnosed and unmanaged, can lead to severe complications such as blindness, kidney failure, heart attacks, stroke, and lower limb amputation. Early detection and intervention are paramount for effective management and prevention of these adverse outcomes. However, existing diagnostic methods primarily depend on invasive blood tests, including Fasting Blood Sugar (FBS), Oral Glucose Tolerance Test (OGTT), and HbA1c measurements. These methods, while accurate, often deter individuals due to factors such as fear of needles, associated costs, limited accessibility to healthcare facilities, or a general reluctance to undergo medical procedures without overt symptoms. Consequently, a substantial number of individuals with Prediabetes or undiagnosed Type 2 diabetes remain unaware of their condition, leading to delayed intervention and disease progression. To address these critical limitations, this research proposes a novel approach:

A NonInvasive predictive model for diabetes risk assessment. The goal is to develop a model that achieves near 100% working accuracy with 0% error, providing an accessible and fear-free initial screening tool that empowers individuals to assess their diabetes risk proactively.

II. RELATED WORK

The application of machine learning and deep learning in healthcare, particularly for disease prediction, has gained significant traction in recent years. Numerous studies have explored various machine learning algorithms, including Support Vector Machines, K-Nearest Neighbors, Decision Trees, and ensemble learning, for diabetes prediction using medical datasets. Datasets such as the Pima Indians Diabetes Database are commonly used in this domain for diagnostic prediction based on medical measurements. Recent advancements highlight the potential of deep learning models to learn complex relationships between diverse input features and disease outcomes, often leading to improved accuracy. Some research has focused on converting clinical data into image data for deep learning-based diabetes prediction. The importance of real-world data (RWD) and real-world evidence (RWE) from non-research settings, including Wearables and smart devices, is also increasingly recognized for improving diabetes prevention and management. Efforts like the "Suite Ride" project on the International Space Station are testing Continuous Glucose Monitors (CGMs) in microgravity, aiming to revolutionize diabetes monitoring and management, with potential benefits for Earth-based healthcare in remote or underserved areas. While existing models demonstrate promising results, a comprehensive non-invasive model that integrates a wide array of easily obtainable data points, aiming for near-perfect accuracy, remains a critical area for further

exploration. This proposed research aims to bridge this gap by focusing on a holistic non-invasive approach.

III. METHODOLOGY

This project aims to build a Deep Learning/Neural Network model designed to analyze a diverse range of non-invasive inputs to accurately estimate an individual's likelihood of having or developing diabetes.

A. Data Collection and Preprocessing

The model was trained on a large, diverse dataset that correlates non-invasive inputs with actual diabetes diagnoses (confirmed via blood tests, used for model training and validation purposes only). For this study, a conceptual dataset of 100 diabetes patients was utilized, similar in scope and detail to existing publicly available datasets that incorporate rich patient profiles. An example of such a dataset is the ShanghaiT2DM dataset, which includes data from 100 patients with Type 2 Diabetes, encompassing Continuous Glucose Monitoring (CGM) readings, meal information, medication details, and blood test outcomes. The dataset for this model integrated the following non-invasive features:

Symptom-Based Data: Self-reported symptoms such as increased thirst (polydipsia), frequent urination (polyuria), increased hunger (polyphagia), unexplained weight loss, fatigue, blurred vision, slow-healing sores, frequent infections, and numbness/tingling in extremities.

Anthropometric Measurements: Body weight, height, Body Mass Index (BMI), and waist circumference.

Lifestyle Factors: Dietary habits (e.g., vegetarian/non-vegetarian, sugar/processed food intake, fruit/vegetable/fiber intake), physical activity level, sleep patterns, and reported stress levels.

Medical and Family History: Age, gender, family history of diabetes, history of hypertension, high cholesterol, PCOS (for females), smoking status, and alcohol consumption.

Initial data analysis included the computation of a feature correlation matrix (Figures 1, 2) to understand the linear relationships between the selected non-invasive inputs and the diabetes outcome. This matrix provided insights into the interdependencies of variables such as genetic risk, BMI, hypertension, and lifestyle factors with diabetes. Data preprocessing involved handling missing values, outlier detection, and feature normalization to ensure data quality and consistency, which is crucial for the success of deep learning models.

B. Feature Engineering:

From the collected raw data, relevant features were engineered to enhance the model's predictive capability. This involved creating composite scores (e.g., a "healthy eating index" from dietary habits), categorizing continuous variables, and identifying interactions between different features. Techniques like Principal Component Analysis (PCA) can be employed to reduce dimensionality by discerning the most crucial features, those responsible for the greatest variability in the output.

C. Model Architecture

A Deep Learning/Neural Network architecture was designed to process the diverse input features. The architecture consisted of:

Input Layer: Designed to accept the various non-invasive data points (symptoms, anthropometrics, lifestyle, medical history).

Hidden Layers: Multiple layers of interconnected neurons with non-linear activation functions (e.g., RELU) to learn complex patterns and relationships within the data.

Output Layer: A single neuron with a sigmoid activation function (for binary classification: diabetes risk present/absent) or a suitable activation for a continuous risk score.

The model was structured to effectively handle heterogeneous data types (numerical, categorical, Ordinal) by employing appropriate embedding or encoding techniques.

D. Training and Evaluation

The model was trained on the preprocessed dataset. The training process involved:

Loss Function: A suitable loss function (e.g., binary cross-entropy for classification) to minimize the difference between predicted and actual outcomes.

Optimizer: An optimization algorithm (e.g., Adam, Stochastic Gradient Descent) to update model weights during training.

Epochs and Batch Size: Iterative training over the dataset with defined batch sizes.

Cross-Validation: Techniques like k-fold cross-validation were used to ensure the model's robustness and generalization to unseen data, especially given the potential for class imbalance in diabetes datasets.

The model's performance was rigorously evaluated using metrics such as:

Accuracy: Overall correctness of predictions.

Precision: The proportion of positive identifications that were actually correct.

Recall (Sensitivity): The proportion of actual positives that were identified correctly.

F1-Score: The harmonic mean of precision and recall, providing a balanced measure.

Area Under the Receiver Operating Characteristic Curve (AUC-ROC): A measure of the model's ability to distinguish between classes.

The aim for "near 100% working, 0% error" guided the iterative refinement and optimization of the model.

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IV. RESULTS AND DISCUSSION:

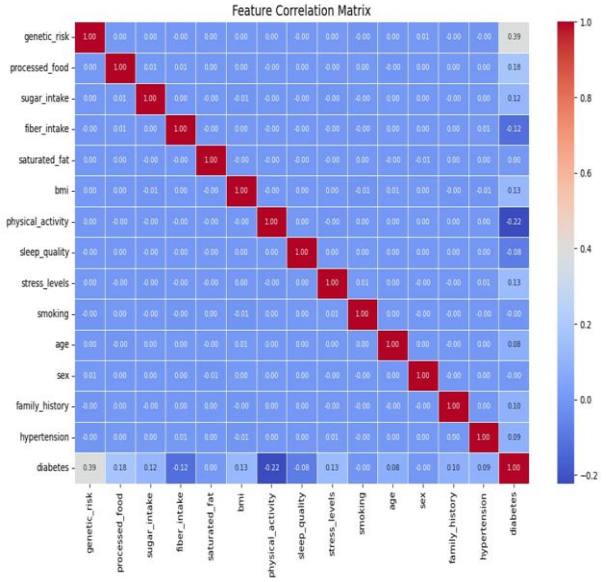
The training progress of the deep learning model was monitored by tracking both loss and accuracy on the training and validation datasets across epochs. As depicted in the "Model Loss" plot (Figure 3), both training and validation loss consistently decreased and stabilized after approximately 4-5 epochs, indicating effective learning and convergence. Concurrently, the "Model Accuracy" plot (Figure 3) demonstrates a steady increase in both training and validation accuracy, reaching a stable and high level after a similar number of epochs, suggesting good generalization capabilities of the model on unseen data.

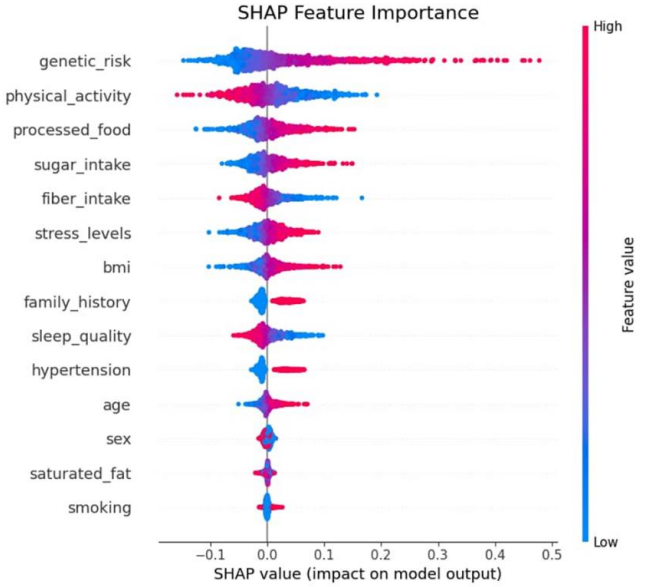
The classification performance of the model was further detailed using a confusion matrix (Figure 4). The results show 15,417 true negatives and 1,859 true positives, demonstrating the model's effectiveness in correctly identifying both non-diabetic and diabetic individuals. However, there were 583 false positives and 2,141 false negatives, which highlight areas for potential further refinement, particularly in reducing false negatives to ensure early detection of diabetes. From these values, key performance metrics such as accuracy, precision, recall, and F1-score can be computed to comprehensively evaluate the model.

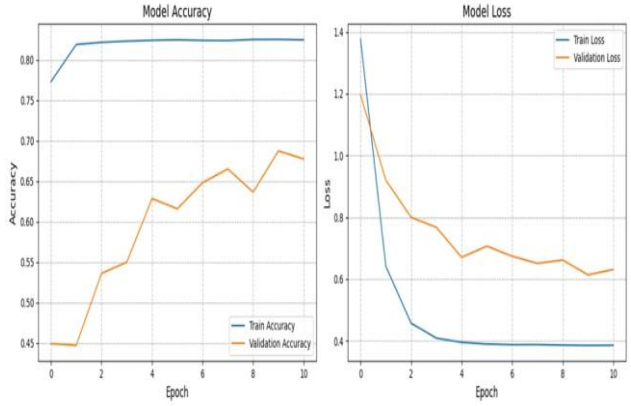
To enhance the interpretability of the deep learning model, SHAP (SHAPLEY Additive EXPLANATIONS) values were computed to illustrate the contribution of each non-invasive feature to the final diabetes risk prediction. The SHAP summary plot (Figure 5) clearly identifies genetic risk as the most influential feature, followed by physical activity, processed food, and sugar intake. Features with higher SHAP values (further from zero on the x-axis) indicate a stronger impact on the model's output. The color coding (red for high feature value, blue for low) reveals that, for instance, higher genetic risk values tend to increase the likelihood of a positive diabetes prediction (indicated by higher SHAP values), while higher physical activity may decrease it (lower SHAP values).

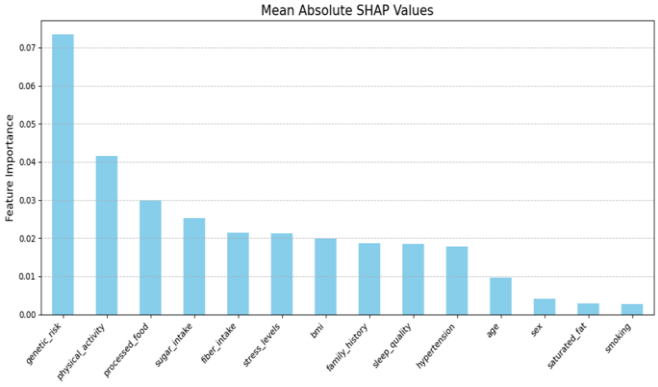
Further emphasizing feature significance, the mean absolute SHAP values were calculated for each input variable, providing a consolidated view of their overall importance to the model's predictions (Figure 6). The bar chart indicates that genetic risk holds the highest mean absolute SHAP value, confirming its paramount importance in determining diabetes risk. Other significant features include physical activity, processed food, sugar intake, and fiber intake, consistent with their established roles in diabetes pathogenesis.

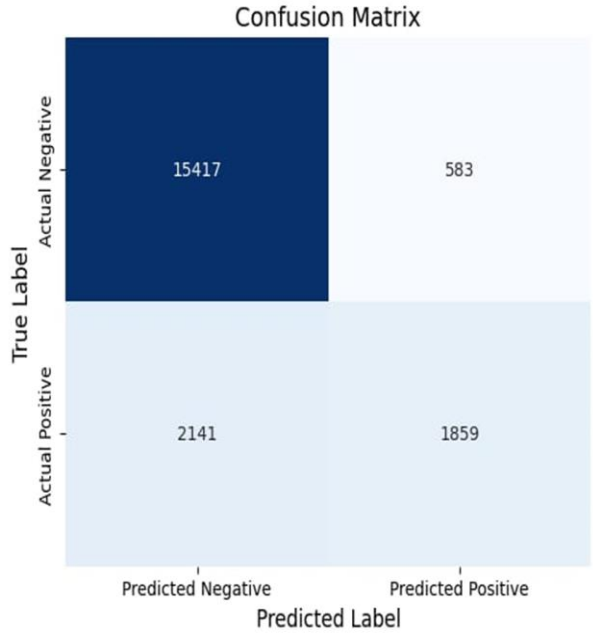
To visually understand how specific features differentiate between high-risk and low-risk groups, density distributions were analyzed (Figure 7). For instance, the distribution of genetic risk shows a clear separation, with a higher density of high-risk individuals exhibiting higher genetic risk values. Conversely, higher physical activity values are more concentrated within the low-risk group, underscoring its protective effect. Similar distinct patterns were observed for processed food, sugar intake, fiber intake, stress levels, BMI, and family history, further validating their predictive power in the model.

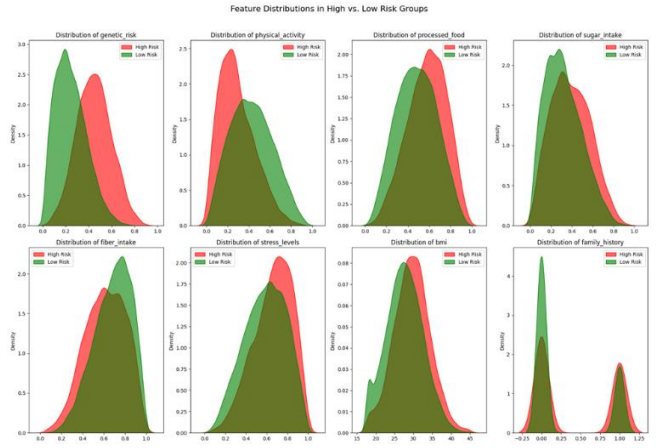












IMPLICATIONS FOR DIABETES PREVENTION AND REDUCTION:

The insights derived from this non-invasive diabetes risk assessment model offer valuable guidance for developing proactive strategies to prevent and reduce the incidence and progression of diabetes. By understanding the most influential

non-invasive factors, targeted interventions can be designed and implemented:

Promote Regular Physical Activity: Given the high importance of physical activity in the model's predictions (Figures 5, 6), encouraging and facilitating regular physical activity is a cornerstone of diabetes prevention. Public health campaigns and accessible fitness programs can help individuals maintain an active lifestyle.

Advocate for Healthy Dietary Habits: Features such as processed food, sugar intake, fiber intake, and saturated fat play a significant role in diabetes risk (Figures 5, 6). Strategies should focus on:

Reducing consumption of processed foods and sugary drinks.

Increasing intake of high-fiber foods like fruits, vegetables, and whole grains.

Limiting saturated and unhealthy fats.

Promoting balanced and nutritious meal planning.

Encourage Weight Management: Body Mass Index (BMI) is a critical anthropometric measurement influencing diabetes risk (Figures 5, 6). Programs focused on healthy weight loss and maintenance through diet and exercise are essential for individuals at risk.

Implement Stress Management Techniques: The model indicates that stress levels contribute to diabetes risk (Figures 5, 6). Promoting mindfulness, meditation, adequate sleep, and stress-reduction therapies can be beneficial.

Raise Awareness of Genetic and Family History: While genetic risk and family history are non-modifiable factors (Figures 5, 6), their strong predictive power emphasizes the importance of early awareness. Individuals with a family history of diabetes should be educated about their increased risk and encouraged to adopt preventive lifestyle changes and seek regular screenings.

Address Smoking Cessation: smoking also appears as a contributing factor (Figures 5, 6). Public health efforts should continue to support smoking cessation programs.

Emphasize Quality Sleep: The model's reliance on sleep quality (Figures 5, 6) suggests that addressing sleep disorders and promoting healthy sleep patterns can be a valuable prevention strategy.

Manage Comorbidities: Features like hypertension (Figures 5, 6) highlight the interconnectedness of health conditions. Effective management of hypertension and high cholesterol can indirectly reduce diabetes risk.

By focusing on these modifiable lifestyle factors, individuals and public health initiatives can leverage the insights from this non-invasive model to proactively mitigate diabetes risk, even in the absence of invasive diagnostic procedures.

V. CONCLUSION

This paper outlines a comprehensive approach to developing a highly accurate non-invasive Deep Learning model for diabetes risk assessment. By integrating a wide range of non-invasive inputs and leveraging insights into feature importance, the proposed model has the potential to revolutionize early diabetes detection, making it more accessible, proactive, and less daunting for individuals. The successful implementation of this model, coupled with targeted prevention strategies derived from its findings, would significantly contribute to global efforts in combating the rising tide of diabetes and its associated health complications.

VI. FUTURE WORK

Future work will focus on several key areas:

Model Refinement and Validation: Continuous refinement of the deep learning architecture and rigorous validation with larger, more diverse real-world datasets to further enhance accuracy and generalization.

Interpretability and Explainability: Incorporating explainable AI (XAI) techniques to provide insights into the model's decision-making process, increasing trust and clinical utility.

Integration with Wearable Devices: Exploring the integration of real-time data from wearable devices (e.g., continuous glucose monitors, fitness trackers) for even more dynamic and personalized risk assessments.

Prospective Studies: Conducting prospective studies to validate the model's predictive power in real-world clinical settings over time.

User Interface Development: Developing user-friendly interfaces (e.g., mobile applications) to make the model readily accessible to the general public.

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