iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80156

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

AI-Powered Hybrid Deep Learning Model for Early Diagnosis of Type-2 Diabetes Mellitus

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Abstract: Type 2 Diabetes Mellitus (T2DM) is a rapidly growing global health concern characterized by long-term complications and high mortality rates. Early diagnosis is essential to reduce risks and improve patient outcomes. This study proposes a hybrid deep learning model that integrates a Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) network for accurate and reliable diabetes prediction. The model is trained on the Pima Indians Diabetes Dataset after systematic preprocessing and normalization. To address the interpretability challenges of deep learning, SHapley Additive exPlanations (SHAP) is incorporated to provide transparent insights into model predictions. Experimental results demonstrate that the hybrid model achieves superior performance compared to individual models, with improved accuracy, recall, and F1-score. The integration of explainable AI enhances trust and usability in clinical environments, making the proposed system a promising solution for early diabetes risk assessment.

Keywords: Type 2 Diabetes Mellitus, Hybrid Deep Learning, MLP, LSTM, Explainable AI, SHAP, Pima Indians Dataset.

I. INTRODUCTION

Type 2 Diabetes Mellitus is a chronic metabolic disorder caused by insulin resistance and impaired glucose regulation. The increasing prevalence of diabetes worldwide has created an urgent need for effective early prediction systems. Traditional diagnostic approaches are often reactive and fail to identify individuals at risk in early stages.

Machine learning techniques such as logistic regression, decision trees, and support vector machines have been widely used for diabetes prediction. Although these models provide reasonable results, they are limited in capturing complex nonlinear relationships among clinical features.

Deep learning approaches have shown improved performance by learning hierarchical feature representations. However, they often function as black-box systems, lacking interpretability. This limitation restricts their adoption in clinical settings where transparency is crucial.

To overcome these challenges, this research proposes a hybrid deep learning framework combining MLP and LSTM architectures. The model captures both nonlinear feature interactions and sequential dependencies. Additionally, SHAP-based explainability is integrated to provide interpretable and trustworthy predictions.

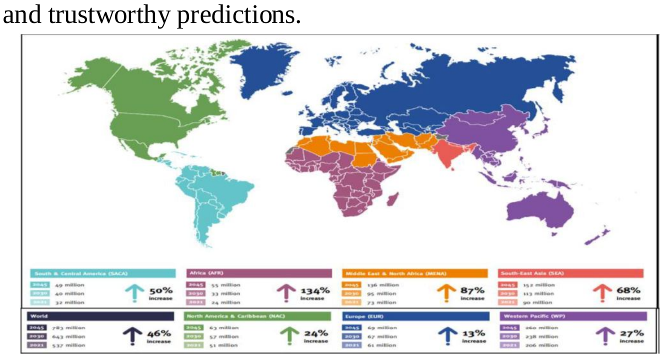

Figure 1:Global prevalence of diabetes and predicted growth trends

II. METHODOLOGY

A. Dataset Description

The study uses the Pima Indians Diabetes Dataset, a widely accepted benchmark dataset for diabetes prediction. It consists of 768 patient records with eight clinical attributes such as glucose level, BMI, insulin, blood pressure, and age. The target variable indicates whether a patient is diabetic or not.

B. Data Preprocessing

To ensure data quality and improve model performance, the following preprocessing steps were performed:

- Invalid values replaced using median imputation
- Feature scaling applied using normalization techniques
- Dataset divided into training and testing sets
- Data reshaped for sequential input in LSTM

C. Model Architecture

The proposed hybrid model integrates two components:

MLP Component

- Handles structured tabular data
- Learns nonlinear feature relationships
- Composed of dense layers with activation functions

LSTM Component

- Captures inter-feature dependencies
- Processes data in sequential form
- Includes dropout layers to reduce overfitting

Hybrid Model

Outputs from both components are combined and passed through fully connected layers to generate the final prediction.

D. Explainability using SHAP

To improve transparency, SHAP is applied to interpret model predictions. It calculates the contribution of each feature to the output, enabling both global and local interpretability. This helps in understanding the importance of clinical parameters in diabetes prediction.

III. RESULTS AND DISCUSSION

A. Performance Evaluation

The performance of the models was evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

Model	Accuracy	Precision	Recall	F1-Score
MLP	85%	84%	83%	83%
LSTM	87%	85%	88%	86%
Hybrid	91%	90%	90%	90%

The hybrid model outperformed individual models in all evaluation metrics, demonstrating its effectiveness.

B. Explainability Results

SHAP analysis revealed that:

- Glucose is the most significant predictor
- BMI and insulin levels strongly influence predictions
- Age contributes moderately to diabetes risk

These results are consistent with established medical knowledge, confirming the reliability of the model.

C. Discussion

The hybrid model successfully combines the strengths of MLP and LSTM. It captures both static and sequential relationships among features, leading to improved predictive performance. The integration of SHAP enhances interpretability, making the model suitable for clinical applications.

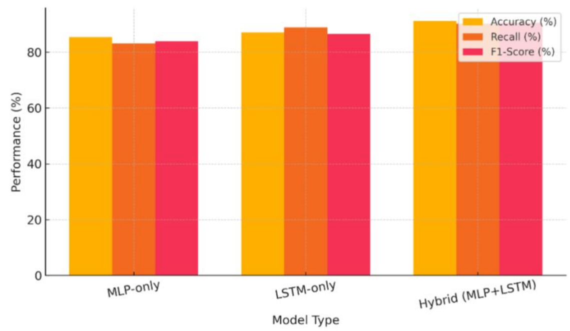

Figure 2 Comparative Performance of MLP-only, LSTM-only, and Hybrid (MLP + LSTM) Models based on Accuracy, Recall, and F1-Score

IV. CONCLUSIONS

This study presents a hybrid deep learning framework for early diagnosis of Type 2 Diabetes Mellitus. By integrating MLP and LSTM architectures with SHAP-based explainability, the model achieves high predictive accuracy and transparency.

The proposed approach addresses key limitations of existing models by balancing performance and interpretability. It provides a practical solution for healthcare systems aiming to implement AI-driven decision support tools.

Future work will focus on incorporating larger and more diverse datasets, real-time monitoring systems, and advanced explainability techniques to further enhance model performance and usability.

V. ACKNOWLEDGMENTS

The authors extend their gratitude to the faculty and research teams at Gyanmanjari Innovative University for their support and valuable insights during this study.

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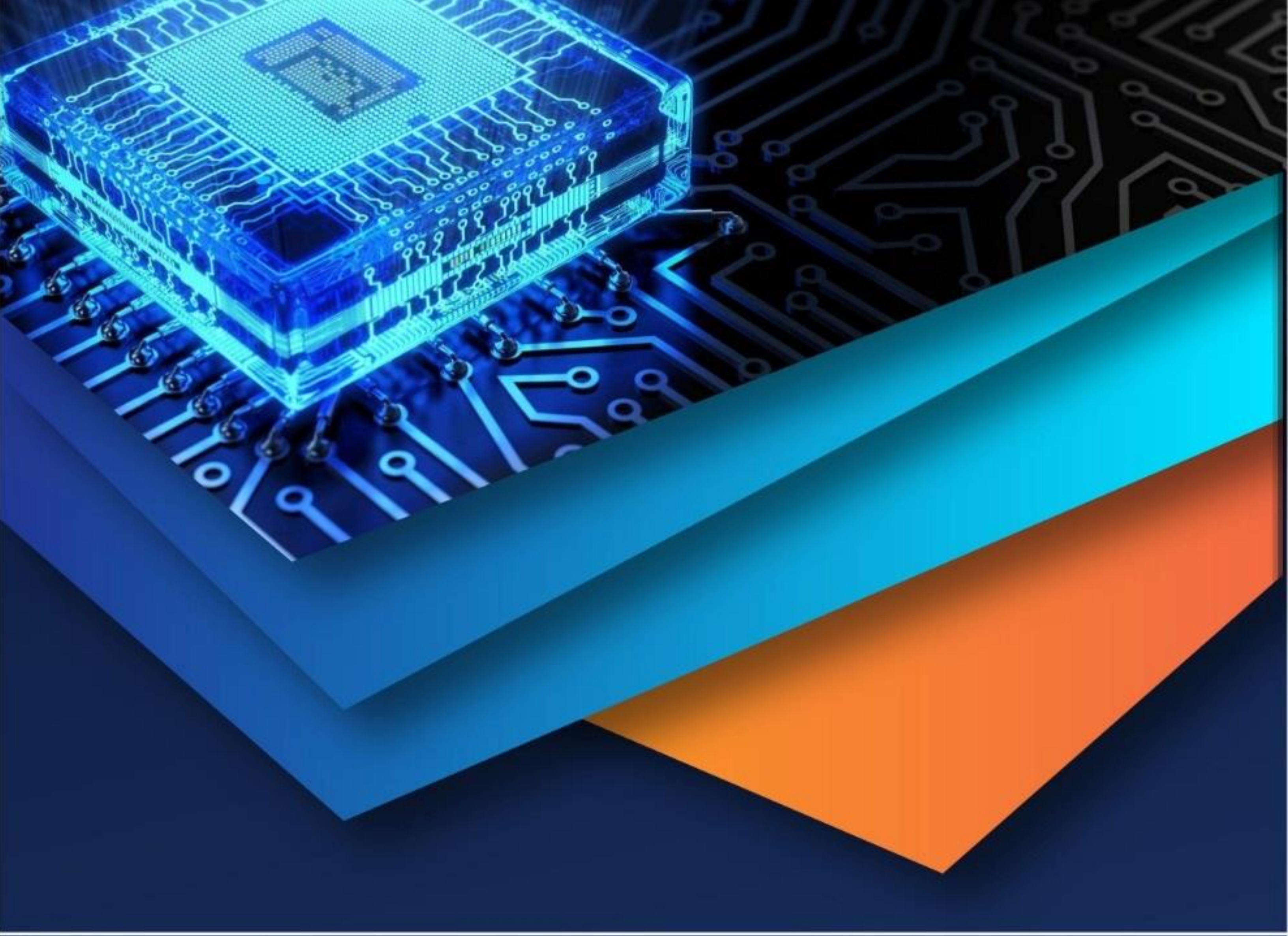

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