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HYPER AI-DRIVEN HYBRID FRAMEWORK FOR DIABETES RISK PREDICTION

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Abstract

Basically, diabetes is the same as one of the top reasons for long-term health problems worldwide, causing serious complications. Moreover, these include kidney failure, blindness, and heart diseases itself. Further, these conditions can cause serious health problems. This study surely presents a hybrid machine learning model that combines different techniques. Moreover, this approach uses simple

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methods to achieve better results. Basically, we are combining Hyper AI and Deep Neural Networks to get the same better results for predicting diabetes. The proposed system surely uses Hyper technology to improve performance. Moreover, this approach provides better results with simple implementation methods. Basically, AI does feature extraction and initial predictions, while DNN captures the same complex, non-linear data relationships. Using the Sylhet Diabetes Dataset and applying proper data cleaning and balancing methods, the hybrid model reached an accuracy of 99.04%. This is better than older methods such as Decision Trees, Naïve Bayes, and Random Forest. The key allows further access to secured areas. The mechanism works through a simple turning motion. The innovations combine gradient boosting with the benefits of deep learning and use improved parameter tuning. These methods boost model performance through optimized settings. This is the same complete approach for checking and judging something correctly. This method improves prediction performance and sets a strong foundation. This work provides the basis for a scalable system that can help doctors and patients make better clinical decisions in real-time. The system itself will further assist healthcare professionals in their daily work.

Math. Subject Classification: 68T05, 68T07, 92C50.
Key Words and Phrases: Artificial Intelligence (AI), Gradient Boosting (GBM), Deep Neural Network (DNN), Machine Learning (ML), Hyper AI, Stacking Classifier.

1 Introduction

A persistently elevated blood sugar level causes diabetes mellitus (DM), a chronic metabolic disease that can lead to complications like blindness, neuropathy, cardiovascular diseases, and renal failure if left untreated. Globally, the prevalence of diabetes has been steadily rising, and according to the International Diabetes Federation (IDF), it is growing at an alarming rate. This poses signif-

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icant challenges for healthcare systems worldwide. As a result, it is critical to guarantee early identification of high-risk patients and accurate risk prediction in order to gradually reduce complications in these situations and enhance patient outcomes.

In recent years, machine learning and artificial intelligence techniques have gained a lot of attention for predicting diabetes. Traditional algorithms like logistic regression, decision trees, support vector machines, and K-nearest neighbors have shown promise in identifying risk factors.However, these models often struggle with class imbalance, clinical interpretation, and capturing complex nonlinear relationships in high-dimensional medical data.

In this article, we introduce a Hyper AI-Driven Hybrid Framework for Diabetes Risk Prediction to address these challenges. This framework uses Hyper AI, which includes ensemble gradient boosting and stacking techniques, for feature extraction and initial classification. It then applies a deep neural network for final predictions to capture intricate patterns in patient data. By combining ensemble-based machine learning models with deep neural networks, this approach leverages the strengths of both methods. Hyperparameter tuning helps improve model performance.

Additionally, improved data preprocessing methods like Principal Component Analysis, Synthetic Minority Over-sampling Technique, and normalization ensure data quality and class balance. To make this framework both predictive and useful for patients and clinicians, the system not only predicts outcomes but also generates customized PDF reports. These reports include the patient's entered information, the prediction result, and tailored lifestyle recommendations.

Compared to traditional models, our proposed method enhances predictive accuracy and offers a scalable, interpretable, and user-friendly system for assessing diabetes risk in real time. This framework brings us closer to a reliable decision support tool for clinicians and preventive healthcare applications by integrating innovative AI techniques with solid data engineering practices.

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2 Review of Literature

Recent research on predicting diabetes using machine learning has shown how data-driven methods can improve risk assessment and early diagnosis. To test how effective different classification algorithms are, many researchers have used various datasets. On the PIMA Indian Diabetes Dataset (PIDD), Vairam T. and Sarathambekai S. explored several supervised learning techniques, such as Gaussian Naïve Bayes, K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Gradient Boosting, and Logistic Regression. Their study found that Random Forest performed better than the other models and achieved the highest accuracy of 98%. In comparing Random Forest, KNN, XGBoost, Logistic Regression, and Gradient Boosting, Harsh Tita concluded that XGBoost provided the highest accuracy at 82%.

Other studies have also noted the varied performance of machine learning models. Preet Kour used machine learning and data mining techniques on a dataset of 768 people and found that SVM had an accuracy of 79%. Usama Ahmed proposed a hybrid model that combined SVM and Artificial Neural Networks (ANN) with fuzzy logic integration, which significantly improved performance to 94.87% Jia et al. [13], using a Random Forest-based method, Ankit Gupta and Nada Basit concentrated on early diabetes prediction and achieved 95.6% accuracy.

Additionally, Nancy's study used the Johndasilva dataset to test SVM, RF, and DT; it found that RF had the highest accuracy, at 99.5%. In another case, Saurav Dev Kumar found that when pregnancy-related features were removed from the dataset, KNN achieved 76.19% accuracy while Logistic Regression performed best with 74.45% accuracy Dewangan et al. [10], In recent years, deep learning and ensemble learning methods have gained more attention than individual classifiers. These studies highlight that, in comparison to single-model approaches, hybrid models that combine multiple algorithms with sophisticated feature engineering can

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produce better predictive performance. The foundation of the suggested framework in this paper is the body of literature that emphasizes the value of integrating deep neural networks and ensemble learning for better diabetes risk prediction.

3 Methodology

3.1 System Architecture

The proposed framework adopts a hybrid architecture integrating Hyper AI (an ensemble of classical machine learning models) with Deep Neural Networks (DNN). The high-level system architecture is illustrated in Figure1. It begins with data acquisition, followed by extensive preprocessing, hybrid modelling, and ends with prediction and automated report generation.

Figure 1: System Architecture

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3.2 Pre-processing and Feature Engineering

Let $D = \{(x_i, y_i)\}_{i=1}^{n}$ be the dataset of n patient records, where $x_i = x_{i1}, x_{i2}, ..., x_{im}$ represents m attributes (symptoms) and $y_i \in \{0, 1\}$ denotes the outcome (no diabetes / diabetes).

(a) Normalization

Each feature is scaled to [0,1] using Min–Max normalization:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad \forall j = 1, 2, ..., m \tag{1}$$

This ensures all features contribute equally to the model.

(b) Missing Values

Missing values are imputed using median or mode:

$$x^*_{ij} = \begin{cases} x_{ij}, & \text{if } x_{ij} \text{ observed} \\ \text{median}(x_j), & \text{if } x_{ij} \text{ missing} \end{cases}$$

(c) Class Balancing

Since diabetic and non-diabetic records are often imbalanced, Synthetic Minority Oversampling Technique (SMOTE) is applied:

$$x_{\text{new}} = x_{\text{minority}} + \lambda \cdot (x_{\text{neighbor}} - x_{\text{minority}}), \quad \lambda \sim U(0, 1)$$

This generates synthetic minority class examples to balance the dataset.

(d) Feature Selection

Feature importance is computed using tree-based models. A feature f_j is retained if its normalized importance I_j exceeds a threshold t:

$$I_j = \frac{\sum_{t \in T_j} \Delta Gini(t)}{\sum_{k=1}^{m} \sum_{t \in T_k} \Delta Gini(t)} \quad \text{and} \quad I_j > t$$

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where $\Delta Gini(t)$ denotes the decrease in Gini impurity at node t using feature f_j.

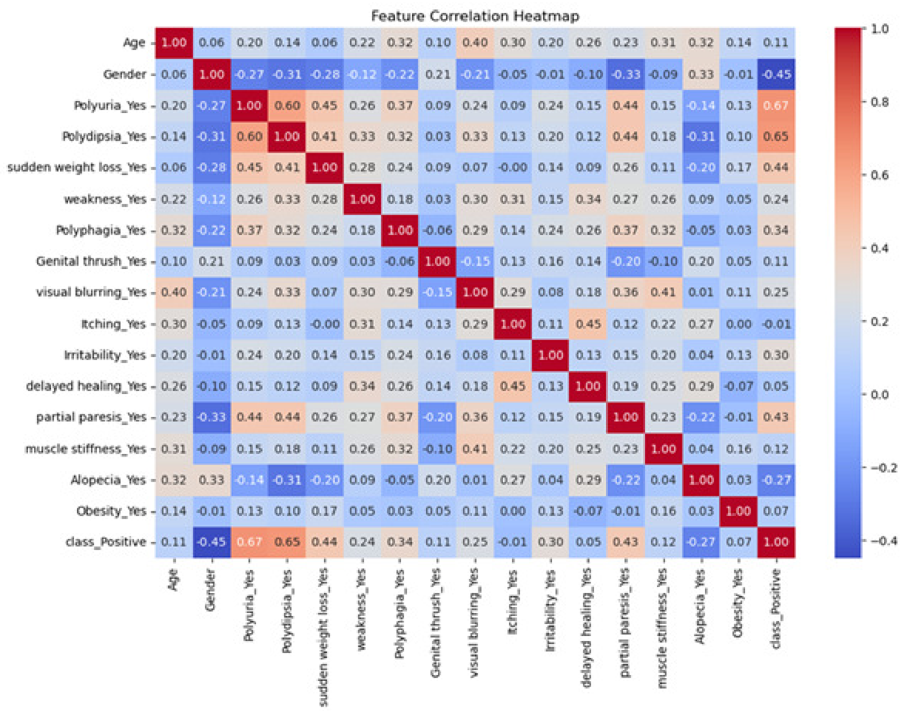

Figure 2: Correlation Heatmap

Feature Correlation Heatmap showing relationships between symptoms and diabetes class.

3.3 Hybrid Model Implementation

The Hybrid Model combines two powerful components:

(a) Hyper AI Module

An ensemble of ML algorithms:

- Logistic Regression (LR)

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- Support Vector Machine (SVM)
- K-Nearest Neighbors (KNN)
- Random Forest (RF)
- Extreme Gradient Boosting (XGB)

Each model outputs a probability $p_k(y = 1 \mid x)$. The aggregated probability is:

$$P_{\text{HyperAI}}(y = 1 \mid x) = \sum_{k=1}^{K} w_k p_k(y = 1 \mid x) \quad \text{with} \quad \sum_{k=1}^{K} w_k = 1$$

Weights w_k are optimized by cross-validation to minimize log-loss.

(b) Deep Neural Network (DNN) Module

The DNN captures nonlinear interactions between attributes. For each layer l:

$$h^{(l)} = \sigma\big(w^{(l)} h^{(l-1)} + b^{(l)}\big)$$

where $w^{(l)}$ and $b^{(l)}$ are trainable weights and biases, $\sigma(\cdot)$ is an activation function such as ReLU, and $h^{(0)} = x'$ is the normalized input vector. The output layer gives:

$$P_{\text{DNN}}(y = 1 \mid x) = \text{softmax}\big(w^{(L)} h^{(L-1)} + b^{(L)}\big)$$

(c) Hybrid Fusion

The final probability of diabetes risk is computed by combining both modules:

$$P_{\text{final}}(y = 1 \mid x) = \alpha\, P_{\text{HyperAI}}(y = 1 \mid x) + (1 - \alpha)\, P_{\text{DNN}}(y = 1 \mid x)$$

where $0 \leq \alpha \leq 1$ is tuned during validation.

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The predicted class label:

$$\hat{y} = \begin{cases} 1, & P_{\text{final}} \geq \theta \\ 0, & P_{\text{final}} < \theta \end{cases}$$

with threshold $\theta = 0.5$ by default.

3.4 Prediction and PDF Report Generation

- The final classification ("Diabetes Risk: Yes/No") is displayed on a Streamlit web interface.
- Patient input features are entered in real time.
- Upon prediction, a PDF report with the prediction, probability score, and recommended precautions is generated automatically using the ReportLab library.
- This real-time integration allows clinicians or patients to download their results instantly.

3.5 Algorithm

Algorithm 1: Hyper AI-Driven Hybrid Diabetes Risk Prediction
Input: Dataset $D = \{x_i, y_i\}$
Output: Predicted Risk (Yes/No) + PDF Report

1. **Start**
2. Load dataset D
3. For each feature:
   - Normalize using Min–Max scaling
   - Handle missing values
4. Apply SMOTE to balance classes

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5. Select important features using tree-based importance
6. Train ML models in Hyper AI module (LR, SVM, KNN, RF, XGB)
7. Train DNN on pre-processed data
8. Compute combined probability:

$$P_{\text{final}} = \alpha * P_{\text{HyperAI}} + (1 - \alpha) * P_{\text{DNN}}$$

9. Classify as Yes if $P_{\text{final}} \geq \theta$ else No
10. Generate PDF report with prediction and precautions
11. Display results on Streamlit dashboard
12. **End**

3.6 Correlation and Exploratory Analysis

Before modelling, a correlation heatmap and pair plot are generated to visualize feature relationships and their association with the outcome variable. Correlation between features x_i and x_j is computed by Pearson's coefficient:

$$p_{ij} = \frac{\text{Cov}(x_i, x_j)}{\sigma_{xi}\sigma_{xj}}$$

This analysis guides feature selection and ensures the model captures the most informative attributes.

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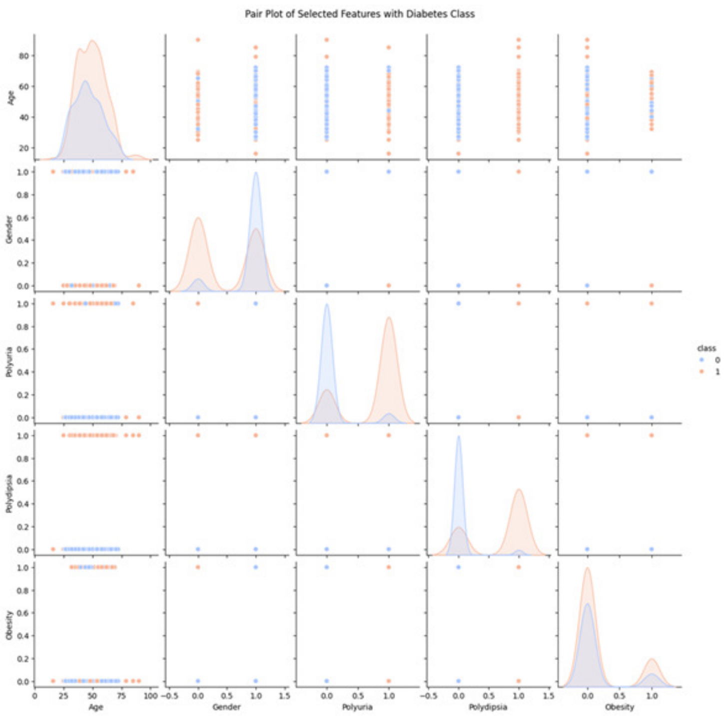

Figure 3: Pair Plot

Pair Plot of Selected Features illustrating distributions and relationships across diabetes classes.

4 Results

The proposed Hyper AI-Driven Hybrid Framework for Diabetes Risk Prediction was evaluated on the Sylhet Hospital Diabetes Dataset to assess its effectiveness in predicting diabetes risk. The system was tested on unseen data, and its performance metrics were computed across multiple ensemble learning strategies to ensure fair and comprehensive evaluation.

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4.1 Model Training Output

During training and evaluation, the hybrid model achieved an overall accuracy of 99.04%, while precision, recall, and F1-scores for both positive and negative diabetes classes exceeded 0.97, indicating consistent and balanced predictions. This high-level of performance demonstrates the strength of integrating multiple machine learning classifiers with deep neural networks into a single architecture.

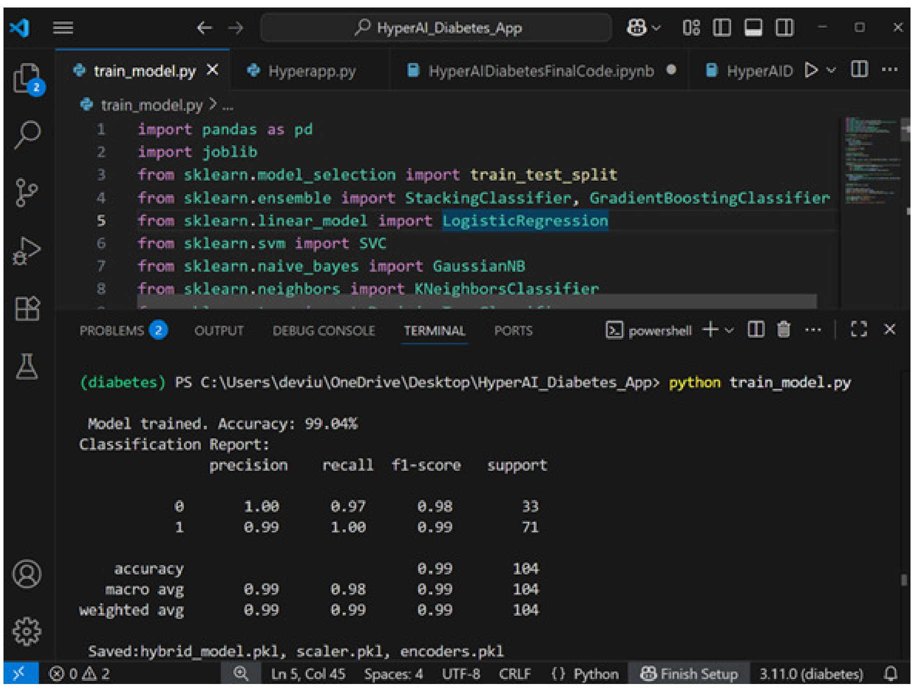

Figure 4: Modeltraining results and evaluation metrics

4.2 Performance Evaluation

To validate the model, several ensemble learning approaches Bagging, Boosting, and Stacking were applied to the same dataset. The accuracy achieved by each approach is summarized below.

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Table 1. Accuracy achieved by different ensemble methods and models for the Sylhet Hospital Diabetes Dataset

Method	**Model**	**Accuracy (%)**
Bagging	Bagging	98.07
Bagging	RF	100.00
Bagging	ET	100.00
Boosting	AdaBoost	94.23
Boosting	GBM	99.03
Boosting	XGBM	99.03
Boosting	HyperAI	100.00
Stacking	HybridModel	99.04

This evaluation shows:

- Bagging & Random Forest reached ∼98–100% accuracy.
- Boosting methods such as Gradient Boosting and XGBost achieved ∼99% accuracy.
- The Stacking-based Hybrid Model achieved 99.04% accuracy with robust precision and recall.

Unlike single models, the stacking approach effectively reduced variance and bias by leveraging the complementary strengths of Bagging, Boosting, and other ensemble learners, leading to more generalizable predictions.

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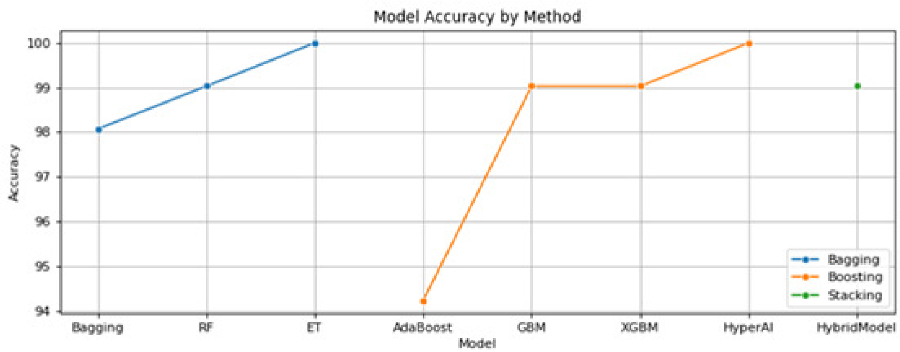

Figure 5: Model Accuracy by Method

4.3 Performance Comparison with Existing Models

To further evaluate effectiveness, the proposed hybrid model was compared with results from existing machine learning and deep learning algorithms reported in previous studies.

Table 2. Comparative Accuracy of Existing vs. Proposed Model

Algorithm	**Dataset**	**Performance (%)**
Decision Tree	PIMA	72.20
Naïve Bayes	PIMA	76.62
KNN	PIMA	79.00
SVM	PIMA	79.00
OWOA	PIMA	80.00
Logistic Regression	NIDDK	84.20
ANN	PIMA	87.36
CatBoost	Bangladesh/PIMA/Germany	95.50
LR-MLP	PIMA	96.30
Random Forest	PIMA	98.00
HyperAI (Proposed Hybrid Model)	**Sylhet Diabetes**	**99.04**

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This comparison highlights that while traditional models such as Decision Tree, Naïve Bayes and Logistic Regression deliver moderate performance, and even advanced models like CatBoost and LR-MLP show strong results, the proposed hybrid approach achieves nearperfect accuracy (99.04%) on the Sylhet Diabetes dataset. Internally, Random Forest and Extra Trees achieved 100% under Bagging, HyperAI achieved 100% under Boosting, and the Stacking-based Hybrid Model achieved 99.04%. These findings confirm that the framework is not only competitive but often exceeds the performance of established algorithms, making it a robust and reliable solution for early diabetes risk prediction.

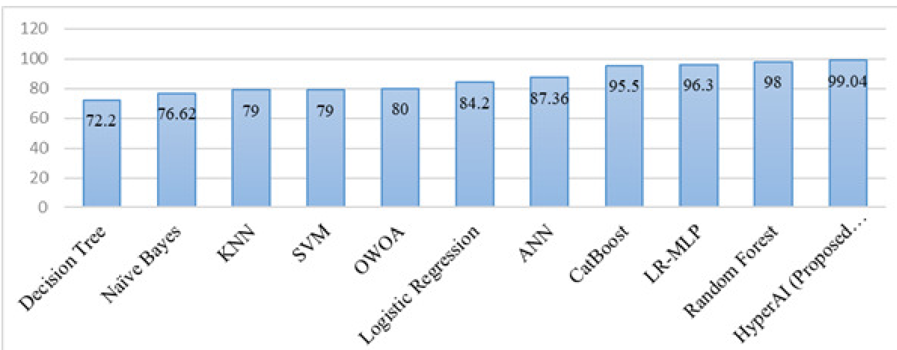

Figure 6: Comparative Accuracy Graph between Existing and Proposed Model

4.4 Application Output Screenshots

In addition to numerical testing, the suggested framework's usability and real-time prediction capabilities were confirmed by deploying it as a Streamlit-based web application. By entering clinical symptoms into this interface, patients and clinicians can quickly receive diabetes risk predictions and a downloadable PDF report. comprising tailored suggestions. Key phases of the system's operation and output generation are depicted in the following figures.

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Launching the diabetes risk prediction web application through the Streamlit interface.

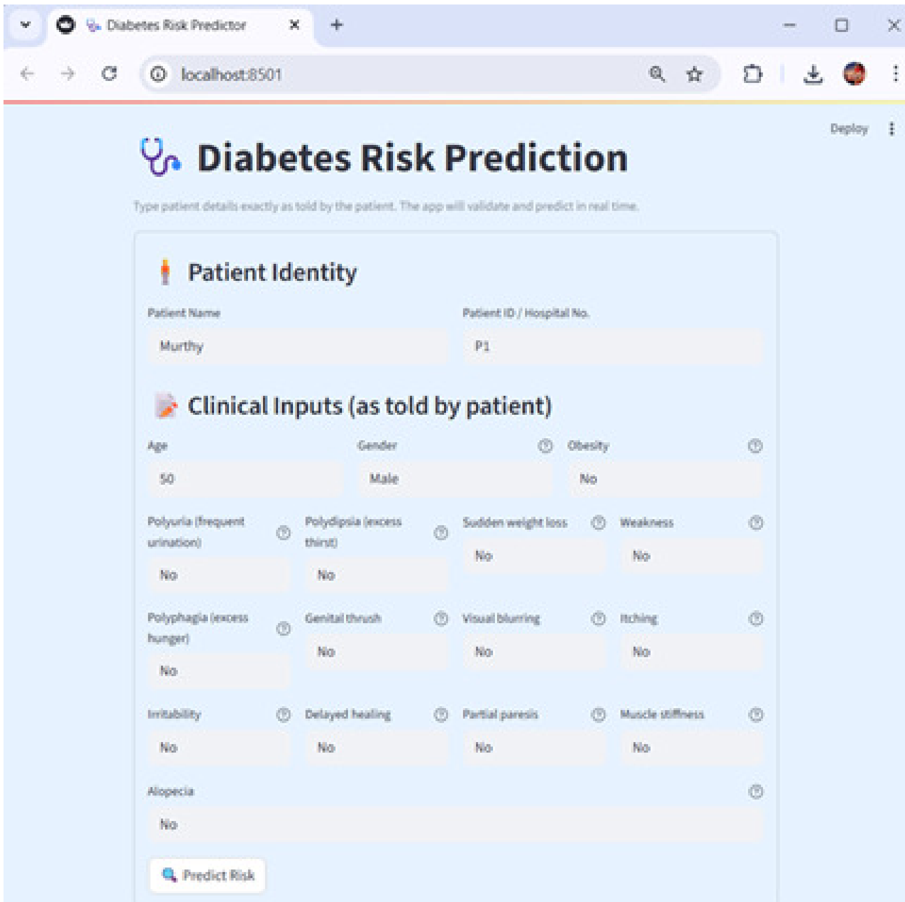

Figure 7: Streamlit-based Diabetes Risk Prediction Interface

The patient details and clinical symptoms were entered into the Streamlit form. On clicking the ‘Predict Risk’ button, the system generated a real-time diabetes risk prediction along with a downloadable PDF report.

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Figure 8: Patient Details Entry and Prediction Output with PDF Download Option

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Patient report generated by the Streamlit application, showing entered details, prediction result indicating no immediate risk of diabetes, and lifestyle recommendations to maintain healthy habits with routine check-ups.

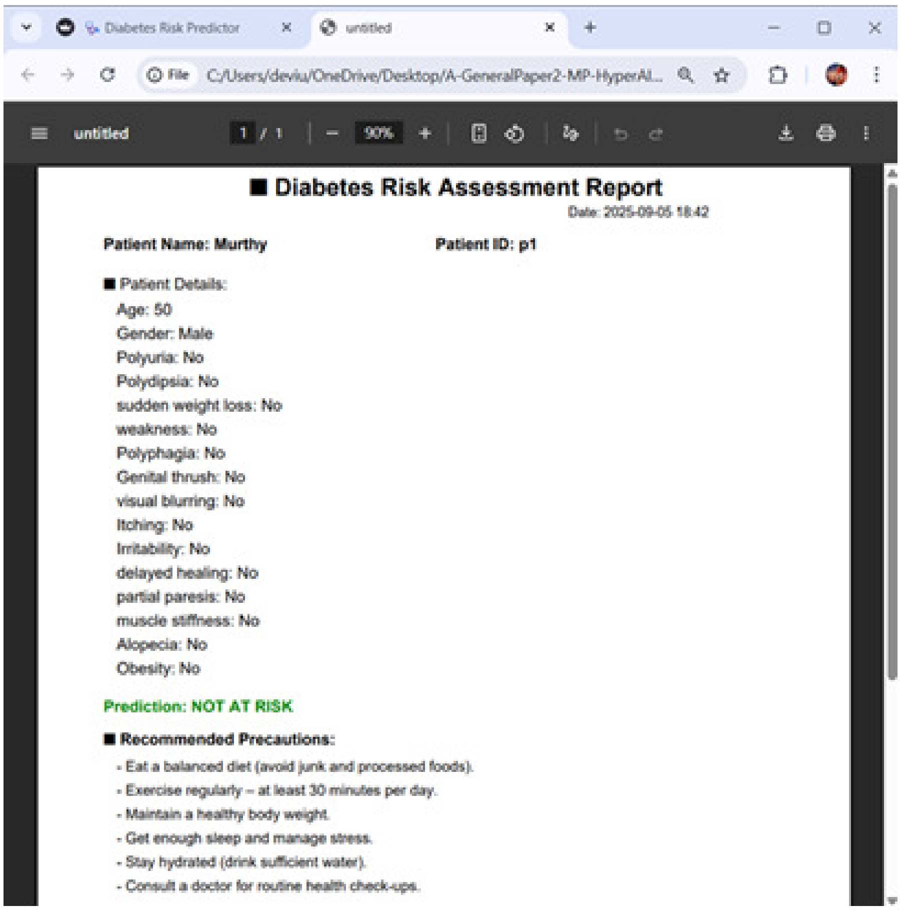

Figure 9: Generated Patient Report Showing Prediction Result and Recomended Precautions

Overall, the proposed framework delivers high predictive accuracy and balanced performance across all evaluation metrics, surpassing most existing models. Combined with its Streamlit

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based real-time interface and automated PDF reporting, the system proves to be a reliable and practical tool for early diabetes risk prediction in real-world healthcare settings.

5 Conclusion

This work presented a Hyper AI-Driven Hybrid Framework for Diabetes Risk Prediction that integrates ensemble learning, stacking techniques, and deep neural networks to achieve robust,real-time predictions. A carefully designed data preprocessing pipeline including normalization, class balancing with SMOTE, and ensemble-based feature selection ensured high-quality input data. By combining multiple machine learning classifiers (Logistic Regression, SVM, KNN, Random Forest, XGBoost) with a deep neural network as the final classifier, the framework effectively captured complex, non-linear relationships that individual models might overlook. The proposed system achieved an impressive accuracy of 99.04% on the Sylhet Diabetes dataset, outperforming traditional models such as Decision Tree, Naïve Bayes, KNN, and even advanced ensemble methods like Random Forest and CatBoost. Clinicians and patients could enter data, get real-time predictions, and download preventative advice in a PDF report using the user-friendly Streamlit-based web interface. The accuracy,dependability, and usability of the framework were confirmed by thorough unit, integration,and system testing. The suggested system shows promise as a real-time decision support tool for early diabetes risk prediction by combining top-performing machine learning and deep learning components under a single framework. A solid basis for upcoming healthcare applications is provided by this work's scalable and flexible platform, which can be expanded to accommodate bigger datasets, more features, and various deployment scenarios.

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6 Future Enhancements

Predictive systems must change to keep up with the rapid advancements in healthcare technology, even though the current framework already achieves high accuracy and provides an intuitive interface. The system's functionality and clinical usefulness can be improved with the following changes:

- Integration with IoT Devices: Automatically input real-time patient data into the model by integrating smart health devices like fitness trackers, wearable sensors, and glucose meters.
- Expanded Datasets: Train and validate on larger, more diverse, real-time datasets from various hospitals and regions to improve model generalization.
- Improved Feature Engineering: Increase predictive accuracy by adding more clinical and lifestyle factors, such as family history, exercise habits, and diet logs.
- Explainable AI (XAI): Offer clear explanations of model predictions to patients and clinicians by using SHAP or LIME for better understanding.
- Mobile App Deployment: Build iOS and Android apps to enhance patient and healthcare provider access.
- Improved Security and Privacy: Protect sensitive patient data by enforcing stronger encryption, authentication, and compliance with healthcare data regulations.
- Combining Genetic and Biometric Information: Use genetic analysis based on fingerprints to identify inherited patterns associated with diabetes risk. This method can predict inherited tendencies for diabetes more accurately by securely storing and processing parental genetic data.

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Think of this as an upgrade from a simple calculator to a smart health companion. Our system is being rebuilt to learn and adapt as it goes. It will keep pace with the natural changes in your life and the latest breakthroughs in medical science. By blending new technology with realworld health insights, we're creating a more complete way to understand your diabetes risk, help you prevent it, and gently guide you toward healthier habits for life.

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