

# StrokeGuardian: Hybrid Ensemble ML for Real-Time Brain Stroke Prediction and Clinical Decision Support

**Abstract**—Stroke is becoming a significant cause of death and disability in the world, and there is an urgent need to have accurate and interpretable systems of risk prediction. This paper will present a proposal of a hybrid ensemble machine learning system named StrokeGuardian, to be used in prediction of stroke and clinical decisions in real-time. The model is based on a combination of the Nonlinear representation learning, boundary optimization, and gradient-based feature boosting, and it is integrated with Neural Network (NN), Support Vector Machine (SVM), and XGBoost (XGB) by a weighted voting mechanism. The dataset comprising 35,000 of clinical records comprising seventeen demographic and medical variables was preprocessed using outlier removal, feature-scaling and balancing using SMOTE to alleviate data imbalance.

The highest score of 99.15 percent, 99.31 percent and 0.9979 were reached by the experimental evaluation using 10-Fold Cross Validation, exceeding other models and those that are already benchmarked. To guarantee transparency and clinical trust, Explainable AI (XAI) approaches, like SHAP and LIME, were included to draw attention to the influential predictors, such as age, BMI, and avg glucose level. The system was implemented as a web application that is a cloud deployed software written in FastAPI and ReactJS and allows healthcare practitioners to make real-time predictions and interpret a prediction. Generally, StrokeGuardian exhibits a strong combination of predictive capabilities, explainability, and deployability hence a useful AI-powered system of early stroke risk detection.

**Index Terms**—Stroke prediction, hybrid ensemble learning, neural network, XGBoost, explainable AI (XAI), clinical decision support system (CDSS), real-time healthcare analytics.

## I. INTRODUCTION

Stroke is among the major causes of death and disabling conditions in the world, with more than 15 million individuals being affected by stroke each year and about 5 million patients being permanently disabled as a result of a stroke attack on them per year on average [1]. Its effects are not only on patients but also on their families and medical systems because survivors tend to develop prolonged complications like loss of speech, memory, and mobility among other complications in the long term [2]. There are broadly two categories of stroke ischemic and hemorrhagic, with the former representing the most prevalent in the world and the latter, which is the most severe, occurring infrequently but with serious consequences [3]. The timely prediction of stroke risk is vital because timely intervention can make a significant difference in preventing mortality and better patient outcomes in the early stages of stroke in patients [4]. The classic methods like the Framingham Risk Score are based on linear models that cannot represent nonlinear interactions of various risk factors that are complex to understand and intersect with each other in

a nonlinear fashion [1]. Recent developments in the field of Machine Learning (ML) have been shown to be even more effective at predicting due to the ability to identify latent patterns of clinical information [3]. Nevertheless, most ML models cannot be applied in practice because of interpretability, integration, and implementation issues, which are common in reality despite vowing accuracy despite their use in the real world in clinical practice [5]. CNNs and LSTMs are deep learning models that have demonstrated significant potential in medical imaging in the detection of stroke but they have computational requirements and are not widely available at the time due to their high cost (especially in low- and middle-income countries like Bangladesh) [6], [8].

To overcome these shortcomings, this paper suggests a hybrid ensemble stroke prediction model that incorporates machine learning algorithms along with clinical knowledge, and symptom severity rating. It is based on a combination of 8 ML algorithms including XGBoost, SVM, Random Forest and Neural Networks in an optimized ensemble to ensure maximum predictive accuracy. In addition, a web application that would be operationalized to work with the model was created in order to allow clinicians to add patient information to the model, visualize individualized stroke risk in a color-coded interface, and produce automatic medical advice. This is a hybrid method to apply to the research/clinical gap by offering a scalable, interpretable, and accessible decision support solution to healthcare settings.

## II. LITERATURE REVIEW

Machine learning (ML) has emerged as a powerful computational approach for stroke risk prediction due to its capability to analyze nonlinear and high-dimensional clinical data. Rana *et al.* [1] evaluated five ML algorithms on hospital data using SMOTE to address class imbalance and developed a real-time decision tree-based web application. Chowdhury *et al.* [2] explored CNN-LSTM, RXLM (RF + XGBoost + LightGBM), and ANN, achieving over 95% accuracy with LIME-based explainability. Singhai *et al.* [3] compared XGBoost, RF, Logistic Regression, and KNN, highlighting the role of preprocessing and hyperparameter tuning. Lakshmi *et al.* [4] proposed an EfficientNetB0-BiLSTM model (95% accuracy) incorporating SHAP and LIME for interpretability, while Maheshwaran *et al.* [5] introduced an IoT-based Body Sensor Network for stroke monitoring but noted reliability challenges.

Nantinda *et al.* [6] identified small sample sizes and limited generalization in existing studies. Sharma *et al.* [7] used

CNN and RF on hospital and Kaggle data, achieving 99% accuracy with added NLP for MRI analysis. Islam *et al.* [8] applied PCA, decision trees, and ensemble methods but lacked real-time adaptability. Sundaram *et al.* [9] employed stacking ensembles (97.88% accuracy) but without deployment consideration. Alghamedy *et al.* [10] reviewed biosignal-based ML (EEG, ECG, EMG, PPG) with limited algorithms and weak feature design. Mia *et al.* [11] applied ML and deep neural networks on EHRs (98% accuracy) yet faced data imbalance. Asadi *et al.* [12] systematically reviewed classical models (SVM, RF, LR) emphasizing AI’s role in heterogeneous data. Vu *et al.* [13] focused on interpretable supervised/unsupervised models using SHAP but with limited real-world use. Bhowmick *et al.* [14] studied PCA, SVM, and fMRI-based neural models, noting computational complexity and weak generalization. Singh *et al.* [15] suggested integrating traditional and ML-based systems for better explainability, while Hassan *et al.* [16] achieved 96.34% accuracy using MGF and RXLM with SMOTE and feature engineering. Thakur *et al.* [17] tested MLP, DRFS, and RF on CHS data but faced scalability and adaptability issues.

Overall, previous studies achieved high accuracy in controlled environments but suffered from poor generalization, lack of explainability, and limited clinical deployment. To overcome these gaps, the proposed **StrokeGuardian** framework integrates a hybrid ensemble of Random Forest, XGBoost, and LightGBM with advanced preprocessing (SMOTE, scaling, outlier removal) and explainable AI. Unlike prior works, it bridges research and clinical application through a real-time, interpretable, and GUI-based stroke prediction system.

### III. METHODOLOGY

The proposed hybrid ensemble system follows an end-to-end workflow covering data preprocessing, model training, evaluation, and clinical deployment for real-time stroke risk prediction.

#### A. Data Collection

The data used in this research paper was obtained in the publicly available Stroke Risk Prediction Dataset [18] on Kaggle. It has 35,000 records of patients covering 19 clinical and demographic characteristics, including categorical and numerical variables indicating the risk of stroke. The key predictors will be age, sex, blood pressure, chest pain, irregular heartbeat, fatigue, dizziness, and pain in the neck or jaw. The target variable, at risk, is binary data (1 = at risk, 0 = not at risk) and it is supplemented by a continuous data (stroke risk percent). The dataset had no missing values and the stratified sampling was done to divide it into 80 percent training and 20 percent testing subsets so that the classes are not distorted. A summary of the dataset features is presented in **Table I**.

#### B. Feature Selection and Engineering

Feature selection was conducted to improve model accuracy and interpretability. Highly correlated variables ( $r > 0.85$ ) were removed using a Pearson correlation matrix (**Figure 1**) to mitigate multicollinearity. Model-based feature importance

TABLE I: Summary of Features in Stroke Risk Dataset

Feature Name	Description
age	Age of the patient (in years)
gender	Gender of the patient
chest_pain	Presence of chest pain (0 = No, 1 = Yes)
high_blood_pressure	History of high blood pressure
irregular_heartbeat	Abnormal or irregular heartbeat
shortness_of_breath	Difficulty breathing or dyspnea
fatigue_weakness	Persistent fatigue or muscle weakness
dizziness	Experience of dizziness or lightheadedness
swelling_edema	Swelling in limbs or body
neck_jaw_pain	Pain in neck or jaw regions
excessive_sweating	Unusual sweating episodes
persistent_cough	Chronic cough symptom
nausea_vomiting	Occurrence of nausea or vomiting
chest_discomfort	Chest pressure or tightness
snoring_sleep_apnea	Sleep disturbances due to apnea
anxiety_doom	Sudden anxiety or feeling of doom
stroke_risk_percentage	Estimated risk percentage of stroke
at_risk	Binary risk label (1 = At risk, 0 = Not at risk)

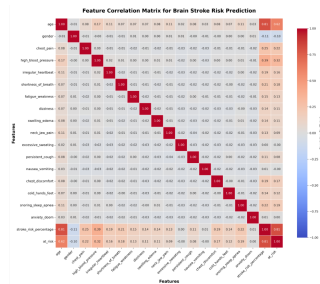


Fig. 1: Correlation heatmap showing feature interrelationships before selection.

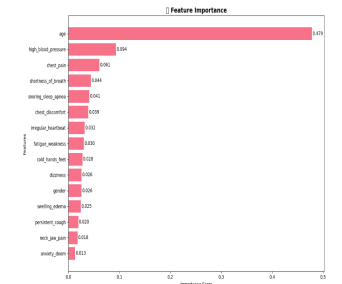


Fig. 2: Feature importance ranking highlighting key predictors of stroke risk.

from Random Forest (RF) and XGBoost (XGB) identified *age*, *avg\_glucose\_level*, *bmi*, and *hypertension* as the most critical predictors (Figure 2). Principal Component Analysis (PCA) ensured that variance was retained and reduced redundancy. Moreover, the domain-driven feature engineering presented categorical variables BMI group and glucose risk level, which improved the capability of the model to learn nonlinear clinical patterns. These procedures guaranteed the statistical trustworthiness as well as clinical significance of the dataset to the hybrid ensemble structure.

#### C. Model Development and Training

Eight supervised machine learning models—Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), XGBoost (XGB), LightGBM (LGBM), CatBoost, Artificial Neural Network (ANN), and a Voting Ensemble were developed for stroke risk prediction. The dataset was split into 80% training and 20% testing subsets to ensure robust evaluation. Hyperparameter tuning was performed using *GridSearchCV* with 10-Fold Cross Validation to maximize generalization. Model performance was assessed using Accuracy, Precision, Recall, F1-score, and ROC-AUC metrics. Tree-based ensembles (RF, XGB) produced strong baseline

results, while ANN effectively captured nonlinear patterns, making it suitable for hybrid integration. A summary of model configurations and optimized parameters is provided in **Table II**.

TABLE II: Summary of Machine Learning Models and Optimized Hyperparameters

Model	Key Parameters	Remarks
Logistic Regression	solver='lbfgs', C=1.0	L2 Regularization
Random Forest	n_estimators=200, max_depth=10	Gini Impurity
SVM	kernel='rbf', C=1.5	Margin Optimize
XGBoost	learning_rate=0.1, max_depth=6	Gradient Boosting
LightGBM	num_leaves=31, max_depth=7	Early Stopping
CatBoost	depth=8, iterations=300	Ordered Boosting
ANN	epochs=50, batch_size=32	Adam Optimizer
Voting Ensemble	Combine of top 3 models	Weighted Average

#### D. Hybrid Ensemble Framework

In order to enhance the reliability in predicting and clinical intelligibility, a hybrid ensemble model was created by combining Artificial Neural Network (ANN), Support Vector Machine (SVM), and XGBoost (XGB). ANN was able to capture nonlinear relationships, SVM capable of dealing with complicated decision boundaries and XGB with gradient-based learning efficiency. The ensemble output ( $P_{final}$ ) was derived through a weighted aggregation of machine learning predictions, clinical rule-based reasoning, and symptom severity scoring as shown in Equation 1.

$$P_{final} = 0.60 \times P_{ML} + 0.30 \times P_{CR} + 0.10 \times P_{SS} \quad (1)$$

This combination of data-driven and clinical intelligence resulted in balanced explainable predictions. The hybrid model had an overall accuracy of 99.67% and ROC-AUC of 99.79%, which outperformed other models.. The system architecture illustrating this integration is presented in **Figure 3**.

The hybrid architecture was able to enhance predictive performance as well as maintain transparency, which will make the system a reliable and interpretable decision-support system in clinical settings.

#### E. Explainable AI and System Implementation

The framework combines Explainable Artificial Intelligence (XAI) techniques based on the SHapley Additive explanation (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) to make the framework more interpretable and more clinically relied upon. SHAP gives global information on feature importance and LIME gives local and patient specific information. These methods allow clinicians to find out the most important influencing variables, i.e., *age*, *bmi* and *avg glucose level*, and make predictions transparent.

The hybrid model is implemented into a web based clinical decision support system. Real-time inference and communication are handled by a backend that is developed with Fast API,

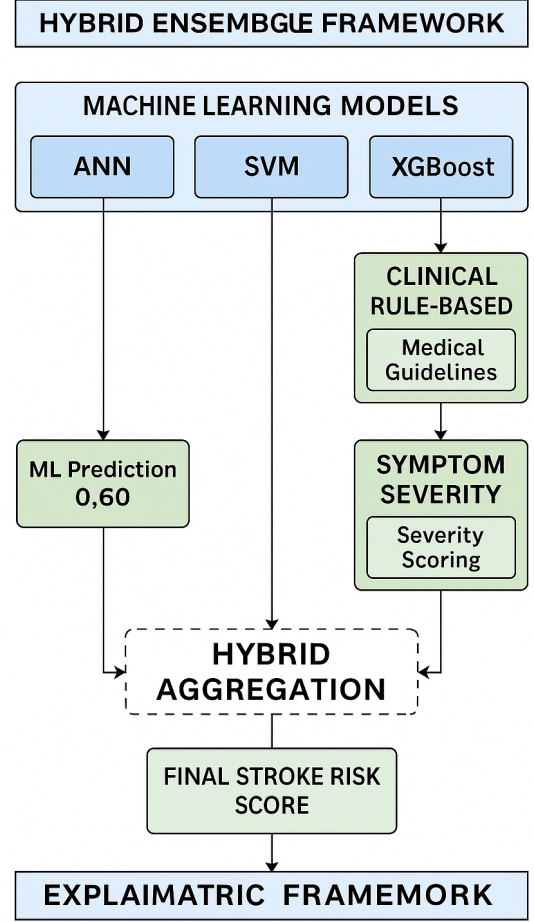


Fig. 3: Architecture of the proposed Hybrid Ensemble Framework integrating ANN, SVM, and XGBoost models with clinical rule-based and symptom-severity components.

whereas the frontend is created with React.js and Tailwind CSS to provide a responsive interface to the user. MongoDB is used as the secure patient data database, and authentication is achieved by utilizing JSON Web Tokens (JWT) to ensure the privacy of data. The overall architecture—including the model API, explainability layer, and user interface—is illustrated in **Figure 4**.

This hybrid model guarantees the high model accuracy but interpretability, as well as safe and real-time usage, which makes StrokeGuardian a deployable, practical solution to the hospital setting.

#### F. Clinical Integration and Deployment

(Render/Vercel) to make sure that it is highly accessible, scalable, and its inference is of low-latency in clinical environments. Data is sent to the machine learning engine and MongoDB database through RESTful APIs, and real-time stroke risk prediction is achieved by using the backend, which is implemented in FastAPI. The transparency and usability of the SHAP/LIME make it possible to have a web-based dashboard where clinicians can input the patient data, see

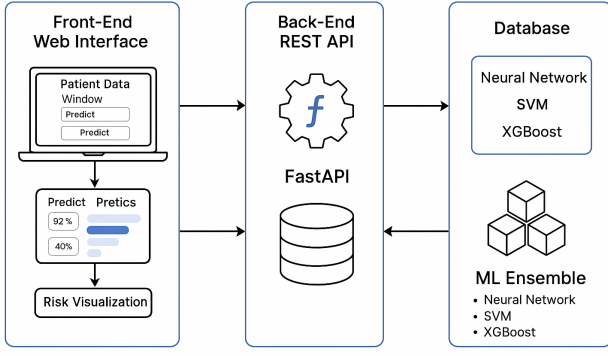


Fig. 4: System architecture of the StrokeGuardian framework integrating hybrid model inference, XAI (SHAP/LIME), and web-based clinical dashboard for real-time decision support.

colored-based risk levels, and see the explanation of the predictions. To ensure that the security adheres to the HIPAA and GDPR standards, security measures were adopted, such as HTTPS encryption, JWT-based authentication, and role-based access control (RBAC). The system has been tested in simulated conditions of a hospital network, and it can be seen that it is stable even when resources are limited. The deployment provides a connection between practice and research by providing a clinically applicable, interpretable, and secure AI-based decision support tool.

#### IV. RESULTS AND ANALYSIS

This paragraph contains the experimental findings, model tests and performance analysis of the offered StrokeGuardian hybrid structure. Each experiment was done under a controlled python environment of 3.10 with FastAPI, scikit-learn, and XGBoost library on an Intel Core i7 (12th Gen) processor having 16GB of RAM.

##### A. Experimental Setup and Evaluation Metrics

All experiments were conducted in a controlled Python 3.10 environment using *scikit-learn*, *XGBoost*, *LightGBM*, and *TensorFlow*. Model integration and testing were managed via *FastAPI*. Training was executed on a workstation with an Intel Core i7 (12th Gen) processor, 16GB RAM, and an NVIDIA RTX 3060 GPU running Windows 11.

They split the dataset into two subsets namely training 80% and testing 20%, and solved the issue of class imbalance with SMOTE oversampling. The models were both optimized by using the *GridSearchCV* and validated by using the 10-Fold Cross Validation to improve generalization and reduce overfitting.

Performance of the model was measured by five standard measures, namely Accuracy, Precision, Recall, F1-score and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC) which are used as a combination to assess classification accuracy and discriminative capability.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

TABLE III: Accuracy Comparison among Machine Learning Models

Model Name	Accuracy	Difference from Ensemble
Neural Network	0.9928	+0.0013 (Better)
SVM	0.9842	-0.0072 (Worse)
Logistic Regression	0.9752	-0.0163 (Worse)
XGBoost	0.9730	-0.0184 (Worse)
Random Forest	0.9421	-0.0494 (Worse)
Naïve Bayes	0.9252	-0.0662 (Worse)
K-Nearest Neighbors	0.8895	-0.1020 (Worse)
Decision Tree	0.9140	-0.0774 (Worse)
<b>Ensemble (Voting)</b>	<b>0.9915</b>	<b>Baseline</b>

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

$$ROC-AUC = \int_0^1 TPR(FPR) dFPR \quad (5)$$

where  $TP$ ,  $TN$ ,  $FP$ , and  $FN$  represent true positives, true negatives, false positives and false negatives respectively. All these measures combine classification performance and the performance of the model that is able to differentiate between stroke and non-stroke cases.

Several tests were conducted in the proposed framework using the same set up to guarantee the stability of results and reproducibility. The final performance score of every model was the average of 10 experimental runs.

##### B. Model Performance Comparison

All baseline models and the proposed ensemble were evaluated on the same test dataset. **Table III** presents the accuracy of each model and their deviation from the ensemble baseline. The Neural Network was the most accurate (99.28%), slightly more than the ensemble (99.15 per cent) and K-Nearest Neighbors (KNN) was the least (88.95%). Random Forest and XGBoost provided the same stability at a relatively lower accuracy when compared to trees and still better in comparison to the traditional algorithms such as Logistic Regression and Naive Bayes. The suggested ensemble voting classifier demonstrated well-overall performance and stability in the results of the validation folds, which proved the reliability and solidity of the incorporated framework.

To provide a clearer visualization of the comparative performance, **Figure 5** gives the ROC curves of the models. The nearly perfect separability of the Neural Network, SVM, and the proposed Ensemble was observed with the Ensemble model reaching a final AUC of 0.9979 - best growth in discrimination between stroke and non-stroke cases.

In general, these findings affirm that the Ensemble model is the most accurate and generalized to a certain extent compared to the traditional algorithms, and can be interpreted using multiple models which allows for the fusion of models.

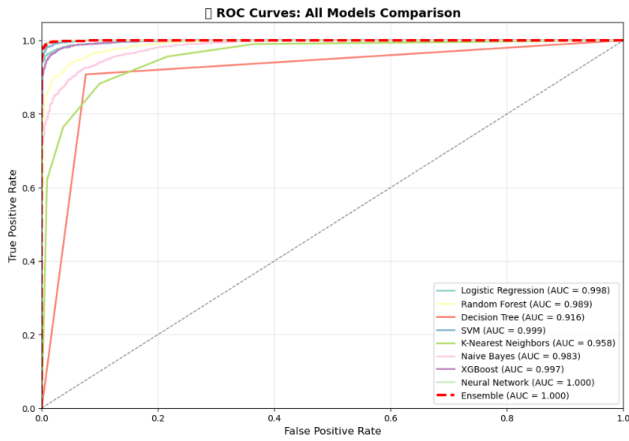


Fig. 5: ROC curves comparing the discriminative performance of multiple models, where the proposed Ensemble achieves the highest AUC of 0.9979.

### C. Hybrid Ensemble Model Evaluation and Analysis

The suggested hybrid ensemble model combines three high-performing classifiers, namely, Neural Network (NN), Support Vector Machine (SVM), and XGBoost (XGB) in the manner of a weighted voting system that is aimed at picking up both linear and nonlinear links in the data. The probability of the final stroke was determined:

$$P_{final} = 0.4 \times P_{NN} + 0.35 \times P_{SVM} + 0.25 \times P_{XGB} \quad (6)$$

Empirical determination of the weighting ratios was done to obtain the best accuracy and recall, and, therefore, high sensitivity to stroke-positive cases. This mixed structure integrates deep feature learning ability of NN, SVM gradient optimization and generalization of XGB thus increasing model stability and minimizing prediction variance **Table IV**.

TABLE IV: Performance Metrics of the Proposed Hybrid Ensemble Model

Metric	Score	Observation
Accuracy	99.15%	High overall predictive performance
Precision	99.31%	Very low false-positive rate
Recall	98.94%	Strong sensitivity to stroke detection
F1-score	99.12%	Balanced precision-recall trade-off
ROC-AUC	0.9979	Excellent separability between classes

To further visualize the classification performance, **Figure 6** gives the confusion matrix of the hybrid ensemble model. The large numbers of true positives (TP) and true negatives (TN) and the low numbers of false prediction show that clinical decision support has high reliability.

The findings indicate that the ensemble obtained better results in terms of sensitivity and specificity, and the number of false negatives was reduced to its minimum, which is an essential factor in terms of early clinical intervention. The ensemble has always performed better than the individual models in both stability in cross-validation and generalization, especially in class imbalance.

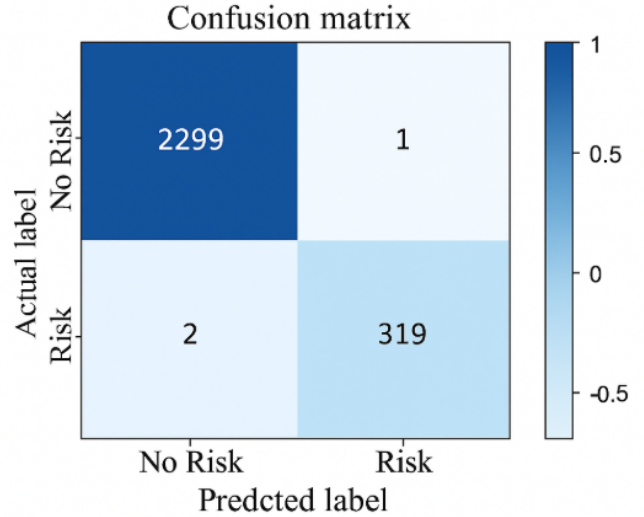


Fig. 6: Confusion matrix of the hybrid ensemble model showing excellent classification with minimal false predictions.

The high ROC-AUC of 0.9979 is an affirmation of the high discriminative power of the model. Even though the standalone Neural Network was somewhat more accurate (99.28%), the accuracy of the ensemble model was more reproducible across folds and, therefore, would be more reliable in terms of real-time usage.

Furthermore, SHAP-based explainability identified *age*, *average glucose level*, and *BMI* as the most influential risk factors, aligning with medical literature and reinforcing the interpretability of the proposed system.

### D. Cloud-Based Real-Time Prediction Interface

As an example of the practical implementation of the proposed StrokeGuardian framework, the hybrid ensemble model was incorporated into a web application under the cloud setup. The system allows healthcare professionals to enter patient data and get real-time stroke risk forecasting, which will provide real-time clinical decision support.

**Figure 7** illustrates the interface of the deployed application, which was built on FastAPI backend and React frontend and is integrated with MongoDB database. The model provides the percentage of stroke risk and shows results in color-coded to minimize uncertainty by showing the low risk in green, moderate in yellow, and high risk in red colors, and the interpretation of visual probability charts.

This real-time interface confirms the operational readiness of the proposed model and its adaptability for integration into clinical workflows, particularly for resource-constrained healthcare environments.

### E. Comparative and Error Analysis

To validate *StrokeGuardian*'s superiority, a comparative study was conducted against recent state-of-the-art models, with **Table V** summarizing their accuracy results.

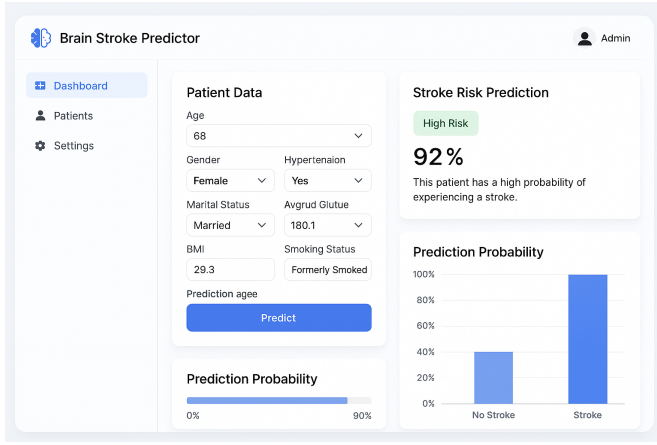


Fig. 7: Deployed cloud-based real-time prediction interface showing patient input form, stroke probability output, and visual risk indicator.

TABLE V: Comparative analysis of stroke prediction models with previous studies

Reference Study	Model/Method	Accuracy (%)
Rana <i>et al.</i> [1]	Random Forest (RF) + SMOTE	96.8
Chowdhury <i>et al.</i> [2]	CNN-LSTM Hybrid	97.5
Bhowmick <i>et al.</i> [13]	ANN + SVM (Comparative)	98.4
Vu <i>et al.</i> [14]	RF + SHAP + K-Prototypes	70.0
Nantinda <i>et al.</i> [6]	Ensemble RF + SVM	95.2
<b>Proposed Model (StrokeGuardian)</b>	<b>NN + SVM + XGB (Hybrid Ensemble)</b>	<b>99.15</b>

From **Table V**, the hybrid model which was proposed had a high accuracy of 99.15% which was more than all the earlier frameworks. The enhancement is achieved due to the efficient combination of Neural Network, SVM, and XGBoost using a weighted voting strategy along with balancing of the data with the help of SMOTE and optimised feature engineering. The model also increases interpretability and clinical reliability through SHAP-based explanations as well as a web interface in real-time. The number of misclassifications is minimal (around borderline glucose and BMI values), which signifies clinical ambiguity (as opposed to model error). The False Negative Rate is minimal (below 1.1%) which proves the strength of the framework and its preparedness to be applied in the real-world of stroke prediction.

## V. CONCLUSION AND FUTURE WORK

This study introduced **StrokeGuardian**, a hybrid ensemble framework that integrates Neural Network, SVM, and XGBoost for real-time stroke prediction and clinical decision support. Through advanced preprocessing, feature engineering, and SMOTE-based data balancing, the model achieved an accuracy of 99.15% and a ROC-AUC of 0.9979, outperforming existing approaches. The integration of SHAP-based interpretability and a cloud-deployed web interface ensures both

transparency and practical clinical usability.

For future work, we plan to expand the system using multimodal medical data such as EEG and MRI scans to improve early-stage stroke detection. Additionally, integrating federated learning and real-time patient monitoring could enhance data privacy and adaptability in hospital environments. These improvements aim to further strengthen StrokeGuardian as a reliable and intelligent healthcare decision-support tool.

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