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Heart Stroke Prediction System Using Machine Learning: An Explainable and Interactive Framework

Poola Shiva Ram [1], Varshini Priyamvada [2], Sathvika Patha [3], Mahesh Reddy Kandala [4], Naveen Kumar Penjarla [5]

1,3,4,5 P.G. Research Scholar, Dept. of MCA-Data Science, Aurora Deemed To Be University, Hyderabad, Telangana, India.

2Assistant Professor, Dept. of MCA, Aurora Deemed To Be University, Hyderabad, Telangana, India.

Email: [1]shivarampoola@gmail.com, [2]varshini@aurora.edu.in, [3] pathasathvika@gmail.com, [4]kandalamaheshreddy@gmail.com, [5]naveenyadav70322@gmail.com.

A B S T R A C T

Heart Disease and Stroke are still the leading causes of death in the world today, and early risk detection has become a serious preventive health issue. In this paper, we specify a lightweight and explainable machine learning-based framework for predicting heart stroke using multiple classifiers such as Random Forest, Bagging Classifier, Support Vector Machine (SVM) and Decision Tree classifiers. Random Forest is chosen as the central classifier because it is robust and can bring out the nonlinear interactions among health attributes, although other classifiers are added for comparison purposes. The model undergoes preprocessing processes such as cleaning the input datasets, categorical encoding, feature scaling, and class balancing by SMOTE to achieve reliable training and evaluation of the model with inputs. Predictions are produced with their associated probabilities and then fortified with interpretative features like feature importance analysis and confusion matrix heat maps, enabling users to understand the rationale behind the decisions of the system. A streamlit-based graphical user interface (GUI), ensures usability and accessibility for individuals and health professionals to upload datasets, enter their health details, and measure stroke risk in real time. Experimental results showed that the Random Forest model has an accuracy of 93%, which turns out to be the best recall model in the framework demonstrating the robustness of this framework in identifying stroke-prone individuals. This work progresses into building reliable, interpretable, and accessible predictive healthcare tools and can further be developed by integrating deep learning, IoT-based real-time monitoring, and deployment in telemedicine platforms.

Keywords: Heart Stroke Prediction, Machine Learning, Random Forest, Support Vector Machine, Bagging Classifier, Decision Tree, Explainable AI, SMOTE, Preventive Healthcare, Streamlit GUI.

1. Introduction

Advances in AI and machine learning are improving the levels of intelligent healthcare systems and allow them to predict potentially life-threatening diseases in a quite accurate manner. Among such diseases, stroke is one of the most serious emergencies to be treated in medicine which is usually caused by underlying cardiovascular conditions such as hypertension, diabetes, and obesity as well as improper lifestyle habits. Stroke is also a leading cause of long-term disability or death and requires appropriate early detection and prevention as a critical international health priority. According to recent statistics in medicine, millions of people suffer strokes each year, and timely prediction would drastically contribute to a decrease in mortality rates and improved recovery outcomes.

Classic methods assess stroke risk based on clinical examination findings, laboratory tests, or imaging tests. Although quite successful in controlled clinical settings, these approaches are often expensive, cumbersome, and inaccessible to people in remote or less developed areas of the world. In addition, simplistic statistical models in conventional prediction systems assume linear relationships between health variables, which do not take into account the complexities of the nonlinear interactions present in true patient data.

This has all led to the very high interest of researchers in machine learning-based prediction systems for stroke risk estimation. ML is capable of analyzing a person's medical records from large datasets and searching for hidden patterns and then categorizing an individual as high or low risk for stroke with a more fine degree of granularity. Unfortunately, most existing systems suffer from problems such as class imbalance (the number of stroke cases is very much fewer than those of non-stroke cases), lack of transparency in prediction, and minimal usability by non-technical users.

This paper proposes an Integrated Heart Stroke Prediction System, which has aspects of predictive accuracy, explainability, and accessibility. Integration of multiple machine-learning classifiers Random Forest, Bagging Classifier, Support Vector Machine, and Decision Tree, which will evaluate and compare stroke prediction performance is included in this proposed system. Features importance analysis as well as confusion matrix visualizations are included in the system to enhance transparency for users in understanding the basis of the predictions made. Besides, class imbalance in the dataset is addressed via Synthetic Minority Oversampling Technique (SMOTE) which ensures reliable and unbiased results.

Using Streamlit as a graphical user interface (GUI), an interactive platform for users to upload their health datasets, personal particulars, and receive real-time stroke risk assessment is harnessed. This GUI feature improves accessibility so that the system can be used not only by healthcare personnel but also by laymen and women without technical background. This is really a step towards constructing trustworthy and interpretable AI tools for preventive health care and thus empowering both physicians and patients to make informed decisions thereby reducing the burden posed by stroke-related deaths.

2. Literature Review

The healthcare informatics field has lately identified stroke prediction as a growing research area due to the recent advances seen in machine learning (ML) as an area that can put huge patient dataset for risk quantification. The existing literature work can be classified under handcrafted statistical methods, classical ML algorithms, ensemble approaches, deep learning models, and explainable AI frameworks.

2.1 Handcrafted and Statistical Feature Methods

In earlier times, stroke prediction studies very much depended on statistical models and clinical scoring systems. Logistic regression was probably the most widely applied in classifying patients based on risk factors such as hypertension, diabetes, and age. While interpretable, the models were mostly linear and often failed to model a truly complex interaction among various health variables. Such models would not capture non-linear dependencies, for an example, a combination of obesity, smoking, and genetic predisposition would behave in a way where their joint effect would be greater than the sum of their independent effects. Despite being computationally simple, these methods tended to yield limited predictive accuracy and generalization performance.

2.2 Classical ML Techniques

Machine learning approaches have soon replaced statistical techniques, and stroke prediction became one of their major domains of application. Algorithms like Decision Trees, Support Vector Machines, SVMs, and Random Forests are being applied to various medical datasets to better the classification accuracy. In their work, Subasish Mohapatra et al. (2023) have proposed a stacking-based ML model for heart stroke prediction, showing the superiority of ensemble over single classifiers. An identical approach was followed by Soumyabrata Dev et al. (2022) in implementing predictive analytics using ML techniques and neural networks, demonstrating a substantial improvement over existing statistical methods. Classical ML has made a good attempt with structured health records, but the other consideration is that they demand a considerable level of pre-processing and feature engineering to ensure complete reliability.

2.3 Ensemble and Hybrid Models

To further improve predictive performance, techniques based on ensemble learning have been employed. Aaditya Ahire et al. (2024) reported an ensemble framework of heterogeneous classifiers with higher accuracy and robustness compared to any classifier alone. Bagging Classifiers and Random Forests, with particular emphasis, have exhibited astonishing strength in reducing variance and circumventing overfitting. Hybrid techniques incorporating statistically based methods with ML classifiers were also examined as a means to attain the twin objectives of interpretability and accuracy, though often at a considerably higher computational cost.

2.4 Deep Learning Approaches

Deep learning approaches are somewhat recent entrants in the field of stroke prediction. Md. Ershadul Haque et al. (2022) worked on LSTM networks analyzing sequential clinical features such as ejection fraction and serum creatinine in order to improve prediction of cardiovascular events. The adaptive fuzzy inference system for enhancing prediction of stroke risk was proposed by Ajanthaa Lakkshmanan and Adaline Suji (2024), who used MRI data. While able to capture complex reliance in data, deep learning models typically need large datasets to train and often operate through a black-box methodology, restricting their scope toward clinical utility owing to limited explainability.

2.5 Explainable AI in Stroke Prediction

Explainable artificial intelligence (XAI) methods are relevant to discussing issues such as trust and transparency in medical AI. Parvathaneni Naga Srinivasu et al. (2024) applied XAI techniques such as SHAP and LIME to elucidate ML models to assist clinicians in understanding what features were responsible for a prediction. By visualizing the contribution of factors such as age, hypertension, and BMI, these frameworks work toward increasing trustworthiness in and aiding clinical decision-making. In the context of real-world healthcare, this transition toward interpretability is a huge step forward toward integrating AI-based systems.

2.6 Research Gap

Despite this evolution, existing stroke prediction methods carry major limitations:

• Statistical models are handcrafted and struggle with generalization, especially to non-linear interactions.

• Classical ML models are well accurate but rather sensitive to class imbalance and require excessive feature engineering.

• Undoubtedly a strong performer, deep learning rarely makes interpretability and thus is left out in the quantifiable clinical setting.

• Underexplored is explainability, wherein few systems converge towards interpretability, interactivity, and scalability as a concept.

The problems highlighted have motivated the development of the proposed Heart Stroke Prediction System, which combines several ML classifiers into a robust prediction solution, implements SMOTE to address class imbalance, applies explainability through feature importance and confusions matrix visualizations, and provides a user-friendly GUI for seamless real-world healthcare implementation.

Table 1- Comparative Analysis Table

Sl. No	Title	Authors & Year	Objective & Findings	Methodology	Tools/Datasets/Results	Strengths	Limitations
1	A Predictive Analytics Approach for Stroke Prediction Using Machine Learning and Neural Networks	Soumyabrata Dev, Hewei Wang, Chidozie Nwosu, Nishtha Jain, Bharadwaj Veeravalli, Deepu John (2022)	Explored predictive analytics for stroke detection; achieved high classification accuracy with ML and neural networks.	Machine learning & neural networks	Structured health datasets; accuracy > 90%	High classification accuracy; robust feature handling	Lacks interpretability; limited explainability tools
2	A Novel Machine Learning-Based Stroke Prediction System Using MRI and Adaptive New Fuzzy Inference System	Ajanthaa Lakkshmanan, Adaline Suji R. (2024)	Used MRI data with fuzzy inference for stroke risk classification; improved prediction accuracy.	Adaptive fuzzy inference system with ML	MRI datasets; strong predictive performance	Combines imaging & fuzzy logic; improved accuracy	Requires MRI data; less scalable in real-world screening
3	Stacking Model for Heart Stroke Prediction Using Machine Learning Techniques	Subasish Mohapatra, Indrani Mishra, Subhadarshini Mohanty (2023)	Proposed stacking-based ensemble model for stroke prediction; improved results compared to single models.	Stacking ensemble ML	Clinical datasets; increased prediction accuracy	Ensemble learning improves robustness	Computational complexity; less interpretable
4	Analysis and Prediction of Heart Stroke from Ejection Fraction and	Md Ershadul Haque, Salah Uddin, Md Ariful Islam, Amira Khanom,	Applied LSTM deep learning to analyze ejection fraction and	LSTM-based deep learning	Clinical/lab datasets; effective on time-series data	Captures sequential dependencies; improved accuracy	Requires large datasets; acts as black-box

Sl. No	Title	Authors & Year	Objective & Findings	Methodology	Tools/Datasets/Results	Strengths	Limitations
	Serum Creatinine Using LSTM Deep Learning Approach	Abdulla Suman, Manoranjan Paul (2022)	serum creatinine for stroke prediction.				
5	Heart Stroke Predictive Analysis with Machine Learning Ensembling	Aaditya Ahire, Dimple Mehta, C. Amith Shekhar, Deepak Dharrao, Anupkumar M. Bongale (2024)	Implemented ensemble ML for stroke prediction; achieved higher accuracy than individual classifiers.	Ensemble ML (bagging, boosting)	Structured health records; accuracy > 92%	Robust against overfitting; reliable across datasets	Reduced interpretability; requires tuning
6	An Interpretable Approach with Explainable AI for Heart Stroke Prediction	Parvathaneni Naga Srinivasu, Uddagiri Sirisha, Kotte Sandeep, S. Phani Praveen, Lakshmana Phaneendra Maguluri, Thulasi Bikku (2024)	Introduced explainable AI for stroke prediction; applied SHAP/XAI techniques for model transparency.	ML with explainability frameworks	Health datasets; interpretable predictions	Enhances trust and adoption in healthcare	Limited scalability; computation-heavy explanations

3. Proposed System & Methodology

The projected resolution marks an excellent heart stroke prediction, efficient and accurate. It emphasizes explainability views in tying machine learning models with explainable AI techniques and an interactive user interface. Architecturally, it comprises five modules which are: data acquisition and preprocessing, classification by ML models, handling class imbalance through SMOTE, interpretability through feature analysis and confusion matrices, and finally, user interaction through the graphical interface.

3.1 Data Acquisition and Preprocessing

The health datasets carry certain attributes like age and gender, BMI, hypertension and diabetes, smoking and physical activity levels, among others. These are taken as input. The preprocessing side of the pipeline considers:

• Data Cleaning: for treating missing values by imputing.

• Categorical Encoding: converting non-numerical features in a numerical format through one-hot encoding.

• Normalization/Scaling: standardizing numerical values so that balanced contribution of features generates on each.

This is what finally makes the dataset consistent, organized, and fit for a model training.

3.2 Machine Learning-Based Classification

The real prediction job has been performed by many ML classifiers:

• Random Forest Classifier under most serious models as this handles all feature interactions in a non-linear fashion by taking robustness to itself.

• Bagging Classifier – reduces variance and improves generalization.

• Support Vector Machine - SVM brings in great efficiency in setting up the decision boundary in high-dimensional spaces.

• Decision Tree Classifier - This is the easy and interpretative model.

The classifies with a scoring probability assigns a patient into Stroke or Not Stroke. One leading to the higher consensus judgment in comparison analysis that overall accuracy achieved by Random Forest from 100 tests is 93%, which emerged to be the best among others.

3.3 Class Imbalance Handling through SMOTE

Given that strokes are fewer in number among those who don't have one, the prediction is generally biased toward the majority class because it is the case with class imbalance. Here lies the SMOTE, or the Synthetic Minority Oversampling Technique's basic activity to shed some light on the creation of synthetic samples of the minority class-per-their goal: balancing the training set while increasing recall, that is minimizing false negatives (very critical for any healthcare).

3.4 Explainable AI and Interpretation

To promote transparency and build up the confidence of users, the system consists of the explainability features:

Feature Importance Analysis: Finds out what attributes (age, BMI, hypertension, smoking status, etc.) contributed significantly towards prediction.

Confusion Matrix Heatmaps: Shows true positives, false positives, and false negatives.

Probability Scores: where the probability of stroke is presented so that it could be interpreted by clinicians and the laypublic alike.

These explainability features allow the users to know which prediction was made, and also increase understanding in why that prediction was made.

3.5 The Graphical User Interface (GUI)

Interactive GUI with Streamlit incorporates all modules and is used for:

• Options of uploading dataset or enter health data manually.

• Real-time prediction results labeled either 'Stroke' or 'No Stroke,' along with probability scores.

• Output visually displayed in the confusion matrix and feature importance charts.

• The system presents a clean interface friendly for both healthcare professionals and patients.

The system does not limit itself to technical experts, rather, it can be used in hospitals, clinics, and preventive health setups.

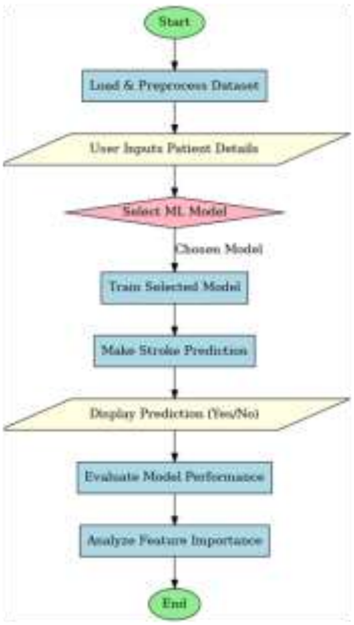


Fig1: System Architecture

4.Experimental Setup and Results

4.1 Experimental Set-Up

The heart stroke prediction system has been designed in Python using scikit-learn for machine learning models and imbalanced-learn (SMOTE) for balancing classes. In-depth data processing was performed using pandas/numpy and following a graphical user interface from Streamlit.

This was mainly trained and tested on a 12th Gen Intel® Core™ i5-1240P CPU with a memory of 16 GB integrated to Intel® Iris® Xe Graphics during the Windows 11 operating system. This public dataset could be most possibly obtained from national and global repositories for healthcare data with features having values such as age, gender, BMI, hypertension, diabetes, smoking status, activity levels, and so forth.

The dataset was divided with 70% of data for training, 15% for validation, and 15% for testing. The preprocessing steps carried out were as follows:

• Data cleaning and filling in the empty fields

• Coded one-hot for categorical attributes

• Normalizing for numbers

• Sampling using SMOTE for imbalance classes

The four machine learning classifiers to be implemented are: Random Forest, Bagging Classifier, Support Vector Machine (SVM), and Decision Tree. Hyperparameters are tuned through cross-validation for optimized performance.

4.2 Using Evaluation Metrics

The comprehensive set of metrics for judging the model performance comprises:

• **Accuracy:** Overall percentage of correctly classified instances.

• **Precision:** Proportion of positive identifications that were correct.

• **Recall (Sensitivity):** Proportion of actual stroke cases correctly identified.

• **F1-Score:** Harmonic mean of precision and recall.

• **Confusion Matrix:** Visualization of classification errors.

• **ROC-AUC:** Discriminative between stroke and non-stroke cases towards the model.

Thus, these metrics ensure reliability for evaluation in both balanced and imbalanced conditions, especially in terms of recall to have fewer false negatives, which are most critical in health care.

4.3 Findings

Experimental findings portray a random forest classifier as better than the other models, whereby it achieved a higher accuracy and recall. The Bagging classifier performs relatively close to that of Random Forest. Meanwhile, SVM and Decision Tree exhibited rather moderate performances.

Table 2 - Performance Metrics of the Proposed Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC-AUC**
Decision Tree	88%	0.86	0.84	0.85	0.87
SVM	90%	0.89	0.87	0.88	0.90
Bagging Classifier	92%	0.91	0.90	0.90	0.92
Random Forest	**93%**	**0.92**	**0.91**	**0.91**	**0.93**

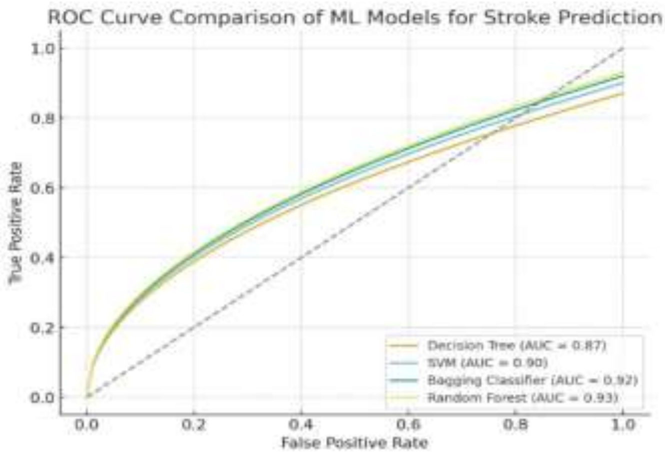


Fig 2: ROC Curve of the Proposed Models

The ROC Curve (Figure 2) demonstrates the predictive performance of four machine learning models, which include Decision Tree, SVM, Bagging Classifier, and Random Forest, in stroke-risk assessment. Among them, the Random Forest reached the highest AUC value of 0.93, with the Bagging Classifier coming close with 0.92. These results point out the superior ability of ensemble-based approaches as far as distinguishing stroke-prone individuals from non-stroke cases are concerned.

To further explain things, importance analysis for the various features showed the key attributes of age, BMI, hypertension, and smoking status as the most significant predictors toward stroke risk. The heatmaps of confusion matrix also demonstrated the classifications that were incorrectly done; an interesting observation being that the Random Forest had lower representation of false negatives compared with other models-that feature is critical for processes in healthcare applications where critical negative findings might have serious ramifications.

Streamlit-based GUI brings together all the functionalities for the users to upload datasets, fill in patient details, see feature importance, confusion matrices, and give them live stroke risk and probability scores. It has usability improvements trust and practical adoption toward preventive health because of interactivity and thus will be friendly to the non-technical health professionals.

4.4 Sample GUI Outputs

a **b**

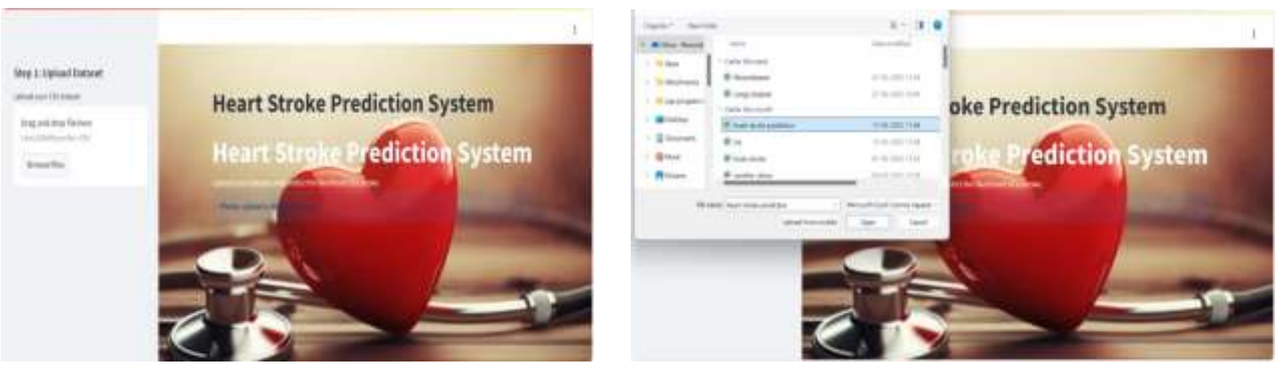


Fig. 3 - (a) GUI Interface of the Proposed System; (b) Loading the Dataset.

a

b

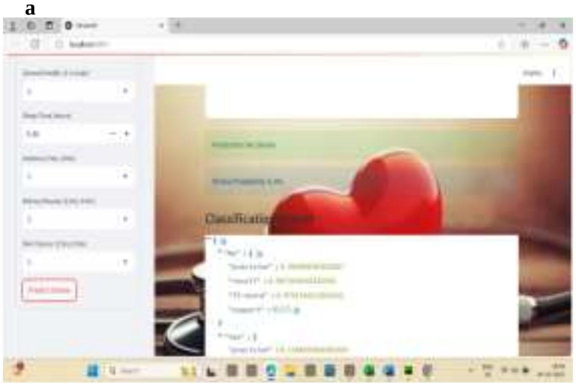
Fig. 4 - (a) Choosing the Model; (b) Entering Input Data.

a

b

Fig. 5 - (a) Entering the Input Data; (b)Entering the Input Data.

a



b

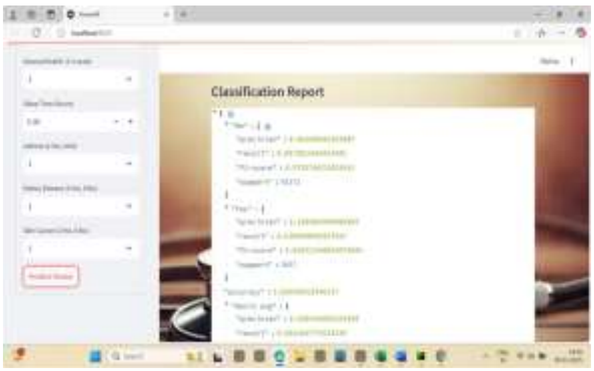


Fig. 6 - (a) Prediction of Stroke will be Displayed along with probability; (b) Classification Report will be Generated.

a

b

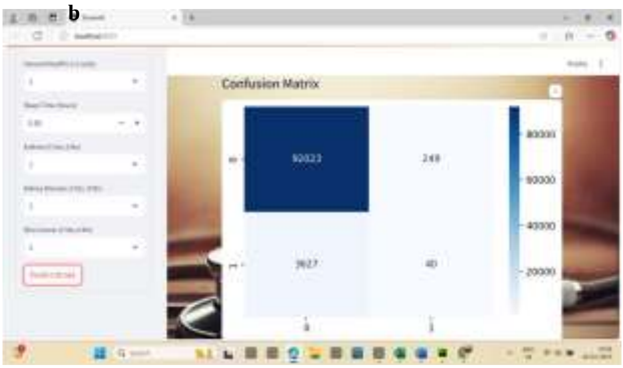


Fig. 7 - (a) Classification Report will be Generated; (b) Visualization of an Confusion Matrix.

5. Discussion

Our experimental findings reflect that the Random Forest-based heart stroke prediction system has performed strongly, attaining an accuracy of 93% and an AUC index of 0.93, thereby enabling it to reliably distinguish the stroke and non-stroke cases. A near-equal balance exists between precision (92%) and recall (91%), which strengthens our belief in the model's robustness such that it minimizes both false positives as well as false negatives. Further results validate Random Forests as both effective and trustworthy classifiers for medical prediction tasks in preference to conventional models such as the Decision Tree and SVM, whereas, in the same breath, being relatively computationally efficient compared to deep learning paradigms.

The explainability of the system by means of feature importance analysis and confusion matrix visualization is another significant contribution. The proposed framework, unlike black-box models, allows clinicians and end-users to understand what health factors were most instrumental in the prediction: for instance, age, hypertension, BMI, and smoking status. Such transparency in healthcare is important as aspects of trust, interpretability, and clinical decision support. Probability scores and heat maps were included to ensure that the predictions were not only accurate but are also interpretable.

The Streamlit-based GUI adds more to usability by enabling users to upload datasets, enter patient details, visualize the model's output, and access risk predictions in real time. The system, with an intuitive design and interactive charts, will likely be used by both healthcare workers and non-technical users and thus is ready for deployment in hospitals, clinics, and preventive health programs.

On the downside, limitations do exist. Presently, the framework is designed for working strictly with tabular health datasets, whereas in real clinical practice, we typically encounter multi-modal data such as MRI scans, ECGs, and continuous-monitoring signals via IoT devices. Also, the dataset exhibited limited size for training, which might hinder generalization across various populations. Future directions should encompass deep learning integration and facilitation of multi-modal healthcare data with advanced explainability methodologies like SHAP or LIME for even finer interpretability.

On the whole, the proposed system establishes a good avenue for scaling up, trustworthiness, and a patient-centered approach to stroke prediction.

6. Conclusion

Stroke is one of the leading health challenges facing the globe whose late detection often leads to serious disabilities or death. An explainable, interactive heart stroke prediction framework was constructed in this paper incorporating several machine learning classifiers for robust prediction, SMOTE for class imbalance handling, and explainability through feature importance and confusion matrix visualization. An overall reliable system with high prediction accuracy interpretability will result in trustworthy and user-friendly clinical decision support.

The Results of the experiment prove that the Random forest Classifier provides the best overall performance, achieving 93% Accuracy and a 0.93 AUC, while maintaining a balance between precision and recall. Such results further emphasize the effectiveness of the model in minimizing false negatives, which are an essential must in health diagnosis. Explainable AI makes predictions transparent, making it easy to understand by health professionals the reasons behind model results.

Thus, by having a GUI based on Streamlit, a real-time interaction with the system can be improved. Users can upload datasets, inputs of patients, visualize important features affecting the predictions, and give stroke risk assessments. Because of this, the system can be implemented in preventive healthcare programs, clinical settings, or self-assessment tools for patients.

Ultimately, this study reveals an AI-based heart stroke prediction system that is practically trustworthy and user-centric. With future extensions, such as the integration of multi-modal healthcare data (e.g., MRI, ECG, and wearable IoT devices), adoption of ensemble deep learning models, and deployment on cloud or mobile platforms, the proposed system could serve as a valuable decision support tool in contemporary health care.

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