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# Automated Stroke Prediction Using Machine Learning

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***Abstract:*** Stroke is a dangerous medical disorder that occurs when blood flow to the brain is disrupted, resulting in neurological impairment. It is a big worldwide threat with serious health and economic implications. To solve this, researchers are developing automated stroke prediction algorithms, which would allow for early intervention and perhaps save lives. The number of people at risk for stroke is growing as the population ages, making precise and effective prediction systems increasingly critical. wo In a comparison examination with six well-known classifiers, the effectiveness of the proposed ML technique was explored in terms of metrics relating to both generalization capability and prediction accuracy. To give insight into the black-box machine learning models, we also studied two kinds of explainable techniques, namely SHAP and LIME, in this study. SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are well-established and reliable approaches for explaining model decision making, particularly in the medical industry. The findings of the experiment revealed that more complicated models outperformed simpler ones, with the top model obtaining almost 91% accuracy and the other models achieving 83-91% accuracy. The proposed framework, which includes global and local explainable methodologies, can aid in standardizing complicated models and gaining insight into their decision-making, which can enhance stroke care and treatment.

***Index Terms* -** Stroke prediction, Explainable Machine Learning, SHAPE, LIME

## I. Introduction

The incidence of stroke has been rising globally, making it one of the leading causes of death and disability. Early intervention is crucial to prevent long-term effects and mortality. However, traditional methods for predicting stroke risk are often time-consuming and error-prone.

Recently, machine learning algorithms have shown significant promise in accurately predicting stroke risk based on various clinical factors. These algorithms can help clinicians identify high-risk patients early, potentially reducing complications and improving outcomes. Moreover, there is a growing need for transparency in machine learning models in healthcare, as interpretable models can provide valuable insights into factors contributing to stroke risk and assist in treatment decisions.

According to the World Stroke Organization, 13 million people worldwide experience a stroke each year, resulting in 5.5 million fatalities. Stroke affects all aspects of a patient's life, including their family, social environment, and work. Contrary to common misconceptions, strokes can impact anyone, regardless of age, gender, or physical health. Strokes can occur suddenly with varying symptoms such as paralysis, numbness, difficulty speaking or walking, dizziness, blurred vision, headache, and in severe cases, loss of consciousness or coma.

This research is motivated by the global increase in stroke incidence and the necessity for early intervention. Traditional methods for predicting stroke risk are time-consuming and prone to errors, often leading to delayed intervention and poorer outcomes. Machine learning algorithms can accurately predict stroke risk based on clinical factors, enabling the early identification of high-risk patients and timely intervention. Furthermore, there is a growing demand for transparent and interpretable machine learning models in healthcare to provide insights into stroke risk factors and aid in treatment decisions.

The goals of this research include exploring machine learning algorithms for stroke prediction, developing an explainable model and web application for clinicians, and enhancing stroke prediction and early intervention to reduce disability and mortality. The study addresses class imbalance in stroke prediction models, identifies important features contributing to stroke risk, and proposes an end-to-end smart healthcare system through an Android application. The effectiveness of the proposed machine learning technique is demonstrated by comparing it with six well-known classifiers in terms of generalization capability and prediction accuracy. Additionally, the study employs SHAP and LIME for model explainability, providing insights into the decision-making process and enhancing the transparency and safety of deep-learning models for medical applications.

In summary, this research aims to develop a trustworthy machine learning model for stroke prediction, address class imbalance issues, identify important stroke risk features, propose an end-to-end smart healthcare system, and demonstrate the effectiveness of the proposed technique. By doing so, it seeks to enhance stroke prediction and early intervention, ultimately reducing the burden of stroke-related disability and mortality.

## II. PRIMARY CONTRIBUTION OF THIS STUDY BRIEFLY OUTLINED AS

### *A.* Machine Learning in Stroke Prediction

Machine learning algorithms are utilized in stroke prediction by analysing patient data, medical histories, risk factors, and outcomes. The goal is to create models that accurately forecast a patient's likelihood of having a stroke, enabling the identification of high-risk individuals for preventative measures. These algorithms can process vast amounts of data to uncover patterns and correlations that may be missed manually, enhancing diagnosis, treatment, and patient outcomes. It covers Machine Learning algorithms like Decision Trees (DT) , Random Forests and Support Vector Machines (SVM) and Deep Learning algorithms like Convolutional Neural Networks (CNNs).

### *B.* Explainable ML in Stroke Prediction

Explainable Machine Learning (XAI) focuses on creating algorithms that offer interpretable and transparent predictions. In the context of stroke prediction, XAI algorithms provide explanations for their forecasts, helping medical practitioners understand the factors influencing predictions and make informed decisions. By elucidating the decision-making process, XAI builds trust in machine learning models and assists in identifying and correcting biases or flaws.

Techniques such as feature significance analysis, decision trees, and attribution approaches are commonly used in XAI for stroke prediction. These methods enhance understanding of the relationships between various risk factors and the likelihood of stroke, aiding in the development of more effective preventative and treatment plans.

The use of XAI in stroke prediction improves the accuracy and reliability of AI-assisted diagnostics, leading to greater confidence in the diagnostic system. XAI frameworks also provide interfaces for domain specialists to offer feedback and justifications, further enhancing model performance and supporting better treatment choices.

## III. Methodologies:

### 1. Dataset Consideration:

| Features | Description | Variable Type |
|---|---|---|
| Gender | Male", "Female" or "Other" | |
| Ever Married | "No" or "Yes" | |
| Work Type | "children", "Govt_jov", "Never_worked", "Private" or "Self-employed" | Categorical Features |
| Residence Type | "Rural" or "Urban" | |
| Smoking Status | "formerly smoked", "never smoked", "smokes" or "Unknown"* | |
| Hypertension | no hypertension = 0, hypertension = 1 | |
| Heart Disease | No heart diseases = 0, heart disease = 1 | |
| Stroke | Healthy = 0, Stroke = 1 | Binary Numerical Features |
| Age | age of the patient | |
| Average Glucose Level | the average glucose level in the blood | Continuous Numerical Features |
| BMI | body mass index | |

**Table 1. Dataset**

We considered above mentioned features for stroke prediction, for which training dataset can be collected from Kaggle dataset. With futuristic model Users health band will feed some of these values (BP, BMI< Heart rate) to model continuously and remaining feature values user has to enter with the help of health checkups.

### 2. Data Preprocessing:

Before developing a model, data pre-processing is necessary to remove noise and outliers that could jeopardize the model's training. This process fixes any flaws that may prevent proper functioning. After acquiring the appropriate dataset, it must be cleaned and structured. The dataset used includes twelve characteristics, with the "id" column deleted. Missing values are examined and filled, with the mean used to fill in the "BMI" column. Label encoding converts string literals into integer values, making the dataset understandable for the computer. The dataset for stroke prediction can be highly skewed. Training a machine learning model with such imbalanced data may result in inaccuracies in metrics like precision and recall. To develop an efficient model, this uneven data must be addressed.

### 3. Feature Engineering

Dataset includes several categorical and discrete features that play a crucial role in risk assessment.
Categorical features include gender, where males are more prone to strokes than females; hypertension, with those having hypertension at a higher risk than those without; and heart disease, with individuals suffering from heart disease being more susceptible to strokes compared to those without such conditions. Marital status is another categorical feature, where married individuals are more prone to strokes than unmarried ones. The working type of an individual also affects stroke risk, with private sector employees facing higher risks due to work stress, followed by self-employed individuals, government employees, and children. Residence type is considered as well, with urban residents having a higher stroke risk compared to rural residents, although stroke mortality is higher in rural areas due to less access to medical treatment. Lastly, smoking status significantly impacts stroke risk, with current smokers at the highest risk, followed by former smokers, and then those who have never smoked.

Discrete features include age, where the probability of having a stroke doubles every ten years after the age of 55. Average glucose level is another critical factor, with high blood glucose levels (ranging from 80 to 200, and commonly above 126) being associated with stroke cases. BMI (Body Mass Index) also plays a significant role, with higher BMI values (ranging from 20 to 40) increasing the risk of ischemic stroke.

The dataset used for stroke prediction is heavily skewed, with a significant bias towards "No Stroke" cases at a ratio of 19:1. To address this imbalance, two primary techniques can be employed. The first is under-sampling, which reduces the number of majority class samples. The second is oversampling, which increases the number of minority class samples. For optimal performance, a combination of both under-sampling and oversampling techniques is recommended.

## IV. ARCHITECTURE:

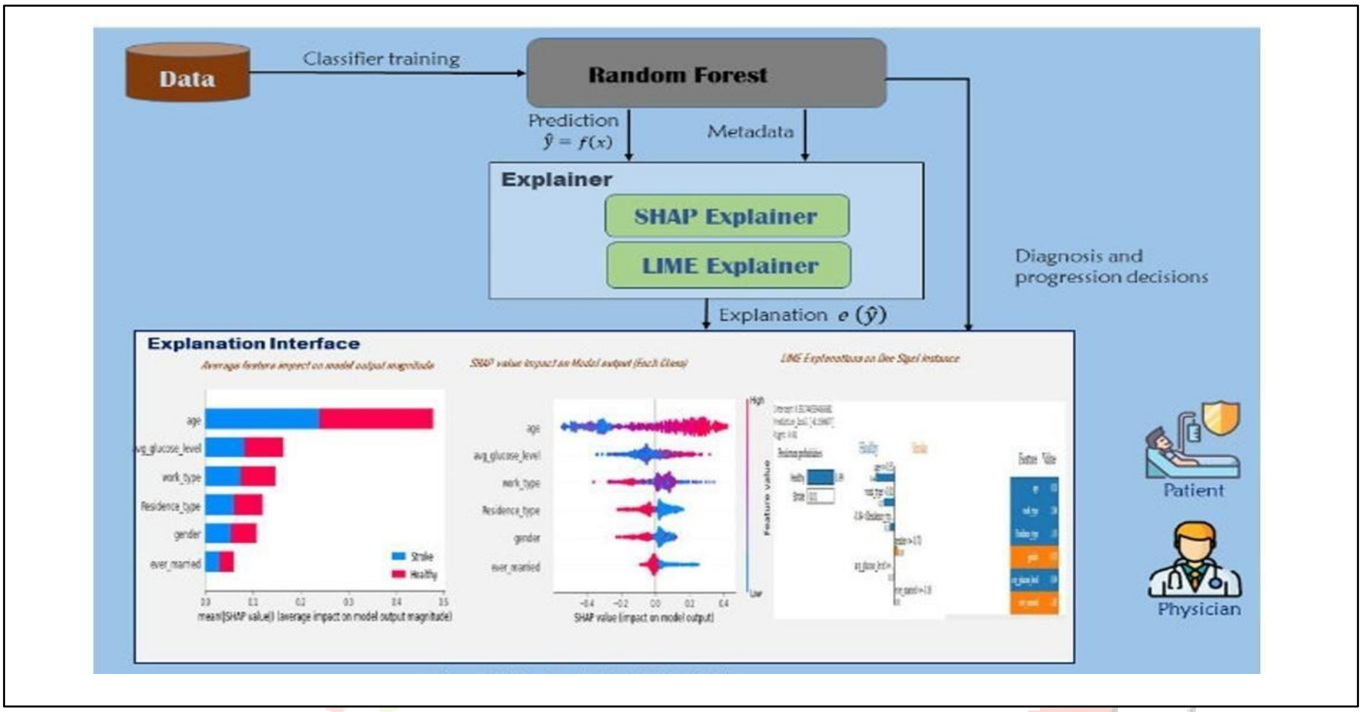


**Figure 1. Role of XAI in stroke prediction**

Explainable Artificial Intelligence (XAI), which aims to create AI systems capable of providing clear and understandable justifications for their predictions and decisions. The main objective of XAI is to develop trustworthy and transparent AI systems that allow users to comprehend their judgments. The article outlines various methods for generating model explanations in XAI, such as feature significance determination, influence analysis, and visual explanations. It also highlights the importance of model explanation in building trust.

Model-agnostic interpretation approaches are emphasized for their ability to generate explanations of complex models while maintaining high prediction accuracy. These approaches are more versatile than model-specific methods as they separate the model from the explanations. Local and global explanation techniques are categorized within model-agnostic strategies, with LIME being a popular local explanation method, and PDP and SHAP being widely used for global interpretation.

LIME works by training local surrogate models to generalize complex models, creating new datasets by altering the current data, and training clear models like decision trees. It compares the prediction performance of the interpretable model and the black-box model. PDP demonstrates the minimal impact of a single feature on the anticipated outcome, showing the relationship between input features and the output.

Figure 1 describes the pipeline of XAI output from Data loading to the patient's question. Here, we introduce LIME and SHAP output got from the model explanation to answer the patient's questions ''how'' and ''why''. No only patients, it is mostly helpful for the physician to interpret our patient report to reach the final prediction.

## V. OUTCOME:

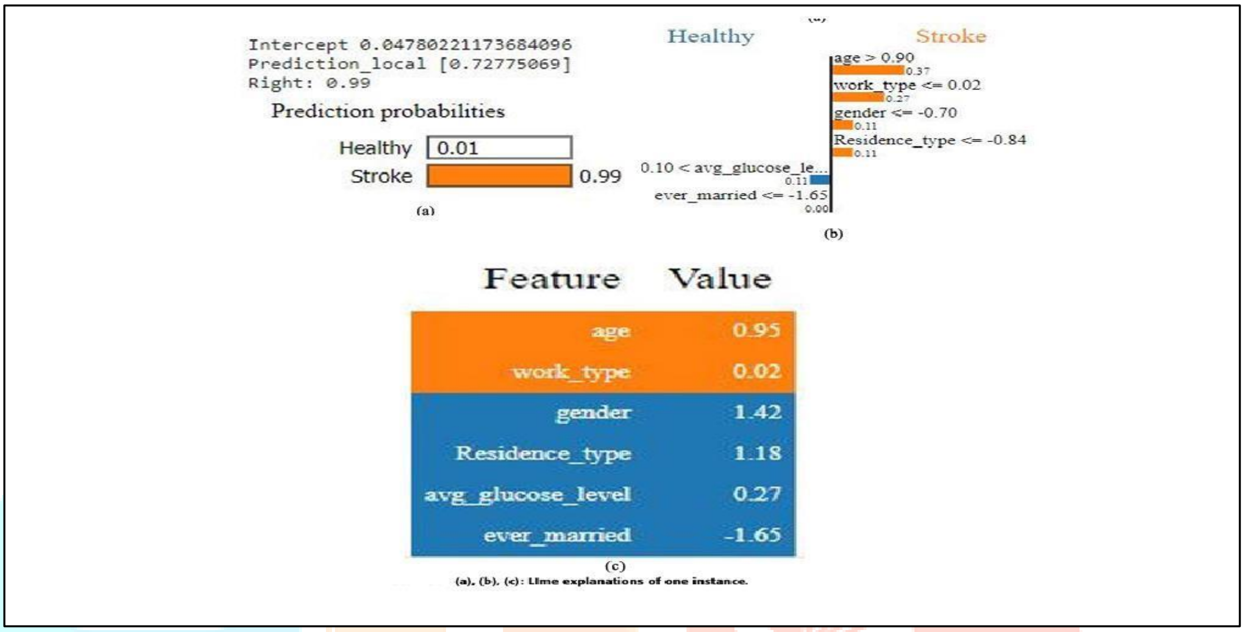


**Fig. 2. Result from LIME model**

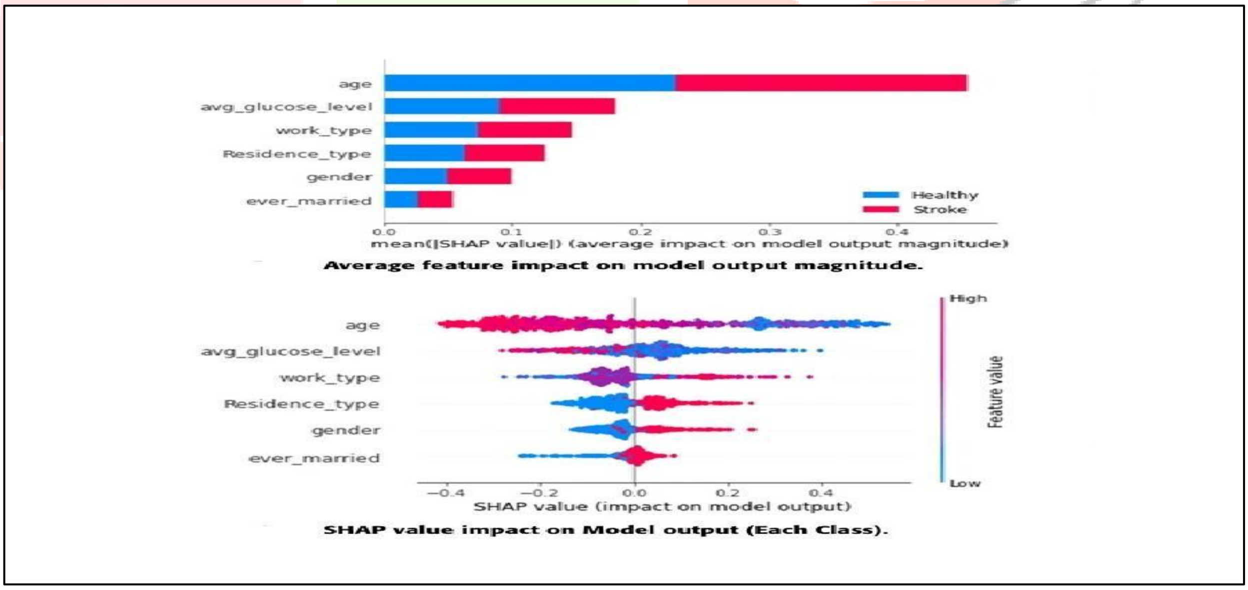


**Fig. 3. Result from SHAP model**

Explainable Artificial Intelligence (XAI) is crucial in medical contexts as it provides concise and accessible explanations for predictions made by machine learning models. XAI approaches, such as SHAP and LIME, are particularly useful in delivering straightforward explanations to patients and doctors who may not have technical backgrounds.

**Pipeline of XAI Output:** [Figure 1] illustrates the pipeline of XAI output from data loading to answering patient questions. LIME and SHAP outputs from the model explanation are used to address patient queries about "how" and "why" certain predictions were made. These explanations are also beneficial for physicians in interpreting patient reports to make final predictions.

**Global Explanations (C.1):** Global explanations ascertain each predictor's effect on the result of a complex model using the Shapley Additive Explanations (SHAP) method. Figure 3 illustrates the common feature impact of the created random forest (RF) classifier, identifying six factors with the greatest effects: age, average glucose level, work type, residence type, gender, and marital status. These explanations align with existing knowledge from experts and literature. Figures 2 and 3 show the random forest classifier's mean feature-importance estimates for each class (0, 1), displayed on the horizontal axis (x-axis) and the attributes ordered by relevance on the vertical axis (y-axis).

**Local Explanations (C.2):** Local explanations provide justifications for individual data points and classifiers. This model-agnostic approach constructs local explanations by creating a collection of changed data points and their corresponding estimates. Figure 2 illustrates two instances of dataset explanations, showing feature values that impact predictions such as "Healthy" or "Stroke." LIME effectively performs local interpretation, explaining the predictions by highlighting important features and information for both physicians and patients.

Average Feature Impact: The average feature impact measures the average effect of each feature on the model's output across all instances in the dataset. It calculates how much the model's output changes when the value of a feature is altered, keeping other feature values constant. This method is typically used for linear models or decision trees and does not consider interactions between features.

SHAP Value Impact: SHAP value impact is a local measure that calculates the contribution of each feature for a specific instance, taking into account interactions between features. SHAP values can be used for any model and provide detailed insights into the model's behavior, especially in multi-class classification problems.

## VI. FUTURE SCOPE:

The study presents a web application for real-time stroke prediction aiming at early intervention. Future work includes developing an end-to-end system accessible via mobile or web application

## VII. CONCLUSION:

A clinical decision support system's Stroke Prediction can serve as a second option in Computer Aided Diagnosis. Although a large research community has helped, these AI based systems can only make predictions and cannot explain their rationale. This is where XAI approaches come in. We demonstrated how to approach Stroke Prediction in a domain-specific manner. For example, if a physician identifies as a Stoke patient but the model labels it as healthy, both the doctor and the patient may wonder ‘‘why?’’ Our method includes explanations such as ‘‘if the age of the patient is between 62 and 84, the prediction confidence in healthy diagnosis drops.’’ The clinician may then notice the age limit in the electronic health records, which is not evident in the disease, and figure out why the model was predicted incorrectly. Whether the clinical decision support system sup ports or opposes the physician's diagnosis, offering human readable reasons fosters confidence and improves system knowledge. Furthermore, our perturbation-based explanation technique for diagnosis employing medically relevant and irrelevant characteristics may have implications in other medical domains

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