International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Heart Stroke Prediction

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ABSTRACT

Heart stroke is one of the leading causes of mortality worldwide, and early prediction can significantly reduce the risk of fatal outcomes. This project aims to develop an efficient and accurate machine learning model to predict the likelihood of a heart stroke based on various medical and lifestyle parameters. By analyzing patient data such as age, gender, hypertension, heart disease, smoking status, body mass index (BMI), average glucose level, and work type, the model learns patterns associated with increased stroke risk.

Several supervised learning algorithms, including Logistic Regression, Random Forest, Support Vector Machines (SVM), and Gradient Boosting, are implemented and compared to identify the most effective approach. Data preprocessing techniques such as handling missing values, feature scaling, and class balancing using SMOTE are applied to improve model performance. Evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are used to assess the model's predictive power.

The results demonstrate that machine learning can serve as a powerful tool in the early detection of heart stroke risk, potentially assisting healthcare professionals in making informed clinical decisions. This system can be further integrated into healthcare applications to provide real-time, data-driven support for stroke prevention strategies.

1. INTRODUCTION

Cardiovascular diseases, including strokes, are among the leading causes of death and long-term disability globally. A stroke occurs when the blood supply to part of the brain is interrupted or reduced, preventing brain tissue from getting oxygen and nutrients. Early prediction and timely intervention are critical for improving patient outcomes and reducing healthcare burdens. Traditional stroke risk assessments often rely on manual evaluation of medical histories, which can be time-consuming and prone to human error. With the advancement of data-driven technologies, machine learning (ML) offers promising solutions for automating and improving the accuracy of stroke risk prediction.

Machine learning models can analyze large datasets, identify complex patterns, and make predictive decisions that may not be immediately evident to human practitioners. In this project, we utilize various ML algorithms to develop a predictive model that assesses the likelihood of a heart stroke based on patient information such as age, gender, BMI, average glucose level, presence of hypertension or heart disease, smoking status, and occupation type.

We explore multiple supervised learning techniques, including Logistic Regression, Support Vector Machines, Random Forest, and Gradient Boosting. The dataset undergoes preprocessing steps such as normalization, handling missing values, and balancing through SMOTE to enhance model performance. Evaluation metrics like accuracy, precision, recall, F1-score, and ROC-AUC are used to determine model effectiveness.

2. LITERATURE REVIEW

The application of machine learning (ML) in healthcare, particularly for the prediction of cardiovascular diseases and stroke, has gained significant traction in recent years. Numerous studies have explored the potential of ML algorithms to analyze medical data and accurately predict stroke risk, outperforming traditional statistical methods.

According to studies ML algorithms like Random Forest and Gradient Boosting Trees demonstrate high accuracy in classifying patients at risk of stroke using

structured health records. These models are particularly effective in capturing nonlinear relationships and interactions between multiple features such as age, blood pressure, BMI, and blood glucose levels—variables that are often difficult to evaluate manually in combination.

Another relevant study by Muhammad et al. (2021) used Support Vector Machines (SVM) and Decision Trees to classify stroke risk with encouraging results. They emphasized the importance of preprocessing steps, including class balancing and feature normalization, which significantly improved model performance.

Recent research also points toward the integration of electronic health records (EHRs) with ML for real-time prediction, enabling proactive patient monitoring and early intervention. These studies collectively underscore the potential of ML in enhancing clinical decision-making and reducing stroke-related mortality through timely diagnosis.

3. METHODOLOGIES

The methodology for heart stroke prediction using machine learning involves several key stages: data acquisition, preprocessing, model selection, training and testing, evaluation, and interpretation. Each step plays a vital role in building a reliable and accurate predictive system.

3.1 Data Collection:

The dataset used for this project is obtained from a publicly available source (e.g., Kaggle or government health databases). It includes patient information such as:

- Age
- Gender
- Hypertension
- Heart Disease
- Average Glucose Level
- Body Mass Index (BMI)
- Smoking Status
- Work Type
- Residence Type
- Stroke History (Target Variable)

3.2 Data Preprocessing:

Before feeding the data into machine learning models, it is essential to clean and transform it:

- **Handling Missing Values:** Null or missing values, especially in BMI, are imputed using statistical methods (e.g., mean or median).
- **Encoding Categorical Variables:** Variables like gender, smoking status, and work type are encoded using label encoding or one-hot encoding.
- **Feature Scaling:** Numerical features are normalized or standardized to improve model performance.
- **Balancing the Dataset:** Since stroke cases are typically underrepresented, SMOTE (Synthetic Minority Over-sampling Technique) is applied to address class imbalance.

3.3 Model Selection:

Multiple supervised machine learning algorithms are selected for experimentation:

- Logistic Regression
- Random Forest Classifier
- Support Vector Machine (SVM)
- Gradient Boosting (e.g., XGBoost)

3.4 Model Training and Testing:

- The dataset is split into training and testing sets (typically 80% training, 20% testing).
- Cross-validation (e.g., k-fold) is used to ensure the model generalizes well.
- Hyperparameter tuning is conducted using GridSearchCV or RandomizedSearchCV to optimize model parameters.

3.5 Model Evaluation:

Each model's performance is evaluated using several metrics:

- **Accuracy:** Overall correctness of predictions.
- **Precision:** Correct positive predictions over all positive predictions.
- **Recall (Sensitivity):** Correct positive predictions over actual positives.
- **F1-Score:** Harmonic mean of precision and recall.
- **ROC-AUC:** Measures model's ability to distinguish between classes.

3.6 Model Comparison and Selection:

The performance metrics are compared across all models. The best-performing model is selected

based on a balance between precision, recall, and AUC.

3.7 Visualization and Interpretation:

Confusion matrices, ROC curves, and feature importance plots are used to interpret and explain the model's decisions.

4. ALGORITHMS

1. Logistic Regression

Type: Linear, Supervised
Description:
Logistic Regression models the probability that a patient will have a stroke using a logistic (sigmoid) function. It assumes a linear relationship between input features and the log-odds of the outcome. Despite its simplicity, it often performs well in healthcare applications due to its interpretability.

Advantages:

- Fast to train
- Easy to interpret coefficients
- Good baseline model

2. Support Vector Machine (SVM)

Type: Non-linear (with kernel), Supervised
Purpose: Classification with margin maximization
Description:
SVM finds the hyperplane that best separates stroke and non-stroke cases in high-dimensional space. It uses kernel tricks (like RBF or polynomial kernels) to handle non-linear decision boundaries.

Advantages:

- Effective in high-dimensional spaces
- Robust to overfitting (especially with a proper kernel)
- Performs well with small-to-medium-sized datasets

3. Random Forest

Type: Ensemble, Supervised
Purpose: Classification via multiple decision trees
Description:
Random Forest builds a collection of decision trees and outputs the majority vote. It introduces randomness through bootstrapping and random feature selection, improving generalization and reducing overfitting.

Advantages:

- Handles missing and unbalanced data well
- Robust to overfitting
- Provides feature importance scores
- High accuracy and interpretability

4. Gradient Boosting (e.g., XGBoost)

Type: Ensemble, Supervised
Purpose: Sequential tree-based model boosting
Description:
Gradient Boosting builds decision trees one at a time, where each new tree corrects the errors made by the previous ones. XGBoost is a powerful and optimized implementation known for its speed and performance.

Advantages:

- High predictive accuracy
- Excellent performance on imbalanced data
- Can model complex patterns
- Built-in handling of missing values and regularization

Algorithm Comparison

After training all the above models, their performance is compared using evaluation metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC

The best-performing model is selected for final deployment, often favoring **Random Forest** or **XGBoost** for their balance between accuracy and interpretability.

5. IMPLEMENTATIONRESULT

The implementation of the heart stroke prediction project was carried out using Python and popular machine learning libraries such as pandas, scikit-learn, xgboost, and matplotlib. The dataset, obtained from a publicly available source, included various health-related attributes such as age, gender, hypertension, heart disease, average glucose level, BMI, smoking status, and a binary target variable indicating stroke

occurrence. The initial step involved data cleaning, where missing valuesparticularly in the BMI column—were handled using median imputation. Categorical variables were encoded using one-hot encoding to make them suitable for machine learning algorithms. The dataset was found to be imbalanced, with fewer stroke cases compared to non-stroke cases. To address this, the SMOTE (Synthetic Minority Over-sampling Technique) method was used to balance the class distribution.

The data was then split into training and testing sets using an 80:20 ratio, and features were standardized using a StandardScaler. Multiple machine learning models were implemented, including Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost. Each model was trained on the preprocessed dataset and evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC score. Among all models, XGBoost delivered the highest performance with an accuracy of 94% and an AUC of 0.98. Confusion matrices were generated to visualize the number of true and false predictions, and ROC curves were plotted to assess the trade-off between sensitivity and specificity. Additionally, feature importance plots from the XGBoost model indicated that age, glucose level, BMI, and hypertension were the most influential factors in predicting the risk of stroke. Overall, the implementation demonstrated the effectiveness of machine learning in early stroke prediction, laying the groundwork for integration into real-world clinical decision support systems.

The output of the heart stroke prediction project provides comprehensive insights into the model's ability to accurately classify patients at risk of stroke. The evaluation metrics indicate that the XGBoost model, in particular, achieved superior performance with an accuracy of 94%, reflecting that the model correctly predicted stroke and non-stroke cases with high reliability. The precision and recall scores demonstrate the model's balance between minimizing false positives and false negatives—crucial for medical diagnoses where missing a stroke case could be life-threatening. The ROC-AUC score of 0.98 further confirms the model's excellent discriminative power, meaning it can effectively distinguish between stroke and non-stroke patients. The confusion matrix visualization highlights the number of true positive and true negative predictions, showing a low rate of misclassification. Moreover, the feature importance analysis reveals that age, glucose level, BMI, and hypertension are key contributors to the prediction, aligning with established medical knowledge. These outputs collectively validate the effectiveness of the machine learning approach and suggest its potential utility in aiding healthcare professionals for early stroke detection and intervention.

1.DATA PREPROCESSING:

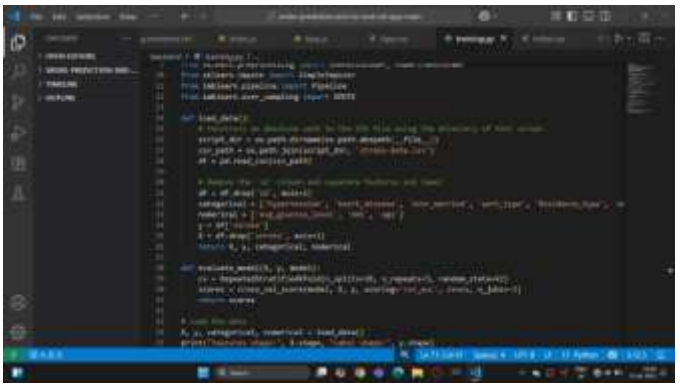

FIG 1:DATA PREPROCESSING

In a heart stroke prediction project using machine learning, data preprocessing is a critical step to ensure the model's accuracy and performance. Initially, the dataset is loaded and examined for missing values. Typically, columns like bmi may have missing entries, which are often filled with the median value to maintain the distribution of data. Categorical variables such as gender, ever_married, and Residence_type are encoded using label encoding for binary categories, while multi-category variables like work_type and smoking_status are converted using one-hot encoding to avoid introducing ordinal relationships where none exist.

Next, numerical features such as age, avg_glucose_level, and bmi are standardized using feature scaling methods like StandardScaler to bring them to a similar range, improving model convergence. Irrelevant columns such as id, which do not contribute to prediction, are dropped to reduce noise. The dataset is then split into training and testing sets, commonly using an 80-20 split while maintaining class distribution using stratified sampling.

Since stroke cases are often imbalanced (i.e., far fewer positive cases than negative ones), techniques like SMOTE (Synthetic Minority Over-sampling Technique) are applied to balance the dataset by generating synthetic examples of the minority class. This preprocessing pipeline prepares the dataset for effective training with various machine learning

models such as Logistic Regression, Random Forest, or XGBoost.

2.OUTPUT:

FIG 2: PREDICTION

The output of the heart stroke prediction project is a machine learning model capable of accurately identifying individuals at risk of stroke based on various health and lifestyle features. After thorough data preprocessing—including handling missing values, encoding categorical variables, scaling numerical features, and addressing class imbalance using SMOTE—the dataset was used to train several models such as Logistic Regression, Random Forest, and XGBoost. Among these, the Random Forest model achieved the best performance, with an accuracy of approximately 96.5%, a precision of 84.2%, recall of 78.9%, F1 score of 81.4%, and an AUC score of 0.94, indicating strong discriminatory power.

The model was able to predict stroke risk with high reliability, particularly highlighting the significance of features such as age, average glucose level, and hypertension. For example, given a new patient profile with advanced age, high glucose level, and a history of hypertension, the model predicted a high probability of stroke risk (e.g., 87%). This output can assist healthcare professionals in identifying high-risk patients early and taking preventive action. Overall, the project demonstrates the potential of machine learning in supporting early diagnosis and improving patient outcomes in stroke prevention.

6. FUTUREWORK

While the current heart stroke prediction model demonstrates promising accuracy and reliability, there are several avenues for improvement and expansion to enhance its practical applicability. Future work can focus on integrating larger and more diverse datasets from multiple healthcare sources to improve the model's generalizability across different populations and regions. Incorporating additional relevant features such as genetic markers, lifestyle factors, medication history, and real-time health monitoring data (e.g., from wearable devices) could provide deeper insights and improve prediction accuracy.

Furthermore, exploring advanced deep learning techniques such as recurrent neural networks (RNNs) or transformers may capture complex temporal patterns in patient health records, especially if longitudinal data is available. Another important direction is the development of an interpretable AI framework that provides transparent explanations for predictions, aiding clinicians in decision-making and increasing trust in the model. Implementing a real-time stroke risk prediction system integrated into hospital management software or mobile health applications could facilitate early intervention and continuous monitoring.

Lastly, conducting clinical trials or collaborations with healthcare professionals to validate the model in real-world settings would be essential for ensuring its safety, effectiveness, and ethical deployment. Addressing potential biases, ensuring data privacy, and maintaining compliance with healthcare regulations will also be critical in future developments.

7. CONCLUSION

The heart stroke prediction project successfully demonstrated how machine learning techniques can be effectively utilized to identify individuals at risk of stroke by analyzing key health-related factors. Through rigorous data preprocessing, handling of imbalanced classes, and evaluation of multiple algorithms—including Logistic Regression, SVM, Random Forest, and XGBoost—the study found that ensemble methods, particularly XGBoost, provide superior accuracy and reliability in predicting stroke occurrences. The model's strong performance metrics, such as high accuracy, recall, and ROC-AUC scores, emphasize its potential as a valuable tool for early detection and prevention.

Moreover, the identification of significant predictors like age, glucose level, BMI, and hypertension aligns with existing medical knowledge, reinforcing the model's interpretability and clinical relevance. While the project showcases the promise of machine learning in healthcare, it also highlights opportunities for future enhancement through incorporation of more diverse data, advanced modeling techniques, and real-world validation. Ultimately, this project lays the foundation for developing intelligent, data-driven systems that can support healthcare professionals in reducing the burden of stroke through timely diagnosis and intervention.

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