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DATA-DRIVEN NEUROLOGY: MACHINE LEARNING APPLICATIONS IN STROKE FORECASTING

[1]*Naga Raju*,[2]*Rajasekhar*
Department of CSE
Birla Institute of Technology and Science (BITS),Pilani

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ABSTRACT:
Brain stroke is a leading cause of mortality and long-term disability worldwide, making early prediction a crucial step in reducing the associated healthcare burden. With the growth of digital health records and advanced computational methods, machine learning (ML) has emerged as a promising approach to identifying high-risk patients before critical events occur. This study explores the potential of machine learning models for stroke prediction by analyzing patient datasets comprising demographic, clinical, and lifestyle factors. Various supervised learning algorithms were implemented, including Logistic Regression, Random Forest, Support Vector Machines (SVM), and Gradient Boosting, with performance evaluated through accuracy, precision, recall, and F1-score. The results highlight the superiority of ensemble-based methods in balancing sensitivity and specificity, suggesting that machine learning can serve as an effective decision-support tool for clinicians. This work underscores the importance of integrating predictive analytics into neurology to move toward proactive and preventive healthcare.

I. INTRODUCTION

Stroke remains one of the most severe neurological conditions, often leading to long-term disability or death if not detected early. Traditional stroke risk assessment methods, such as clinical scoring systems, provide valuable insights but often fail to capture complex nonlinear relationships among risk factors such as hypertension, diabetes, smoking, obesity, and cardiac conditions. With the increasing availability of large-scale medical datasets, machine learning has the potential to address this gap by uncovering hidden patterns and correlations that traditional methods overlook. Data-driven approaches provide the opportunity not only for improved stroke prediction but also for enabling personalized risk stratification. This study investigates the application of machine learning models to forecast stroke risk, aiming to demonstrate the advantages of predictive modeling over conventional clinical assessments.

II. LITERATURE SURVEY

In recent years, researchers have explored various computational approaches to predict stroke risk. Ali et al. applied decision tree algorithms on healthcare datasets and demonstrated moderate accuracy in identifying high-risk individuals. Similarly, Tang et al. employed logistic regression and neural networks, highlighting that neural networks outperformed traditional statistical methods in handling large and nonlinear data. Ensemble learning methods, particularly Random Forest and Gradient Boosting, have shown strong predictive power due to their ability to manage class imbalance and reduce overfitting. Additionally, studies integrating electronic health records (EHRs) with ML algorithms suggest that incorporating lifestyle and demographic data improves prediction performance. Recent advancements also include deep learning architectures capable of analyzing medical imaging for stroke detection, though these remain computationally intensive and less interpretable. Overall, the literature indicates that machine

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learning is a promising frontier in stroke prediction, though challenges such as data imbalance, feature interpretability, and real-world clinical deployment persist.

III. EXISTING SYSTEM

The existing stroke prediction systems are mostly based on traditional statistical models like logistic regression or simple machine learning techniques such as decision trees. These systems rely heavily on clinical data (age, blood pressure, diabetes, smoking status, etc.) and use fixed rules or predefined features for risk assessment. While they provide some level of prediction, their overall accuracy and adaptability are limited.

DISADVANTAGES

Low Predictive Accuracy – Traditional models cannot capture complex, nonlinear patterns among stroke risk factors.

Poor Generalization – Models trained on a specific dataset often fail when applied to different populations or larger datasets.

Limited Interpretability – Predictions are given without clear explanations, making it difficult for clinicians to trust the results.

Imbalance Sensitivity – Existing models perform poorly with imbalanced datasets where stroke cases are much fewer than non-stroke cases.

Lack of Real-Time Adaptability – Current systems cannot update dynamically with new patient data or integrate continuous monitoring from wearable devices.

PROPOSED SYSTEM

The proposed stroke prediction system leverages advanced machine learning techniques, particularly ensemble models such as Random Forest, Gradient Boosting, and XGBoost, to improve prediction accuracy and reliability. The system incorporates data preprocessing methods like normalization, feature selection, and SMOTE for class balancing, ensuring fair learning from imbalanced medical datasets. Additionally, explainable AI (XAI) techniques are integrated to provide interpretable predictions, allowing clinicians to understand which risk factors contribute most to stroke occurrence. Unlike traditional methods, the proposed system is designed to adapt to real-time health data from electronic health records (EHRs) and wearable devices, making it more suitable for preventive healthcare.

ADVANTAGES

High Predictive Accuracy – Advanced ML algorithms capture complex nonlinear relationships among risk factors, improving reliability.

Better Generalization – The system performs well across diverse and large-scale datasets, making it more robust.

Interpretability with Explainable AI – Clinicians can understand feature importance and trust the predictions.

Effective Handling of Imbalanced Data – Techniques like SMOTE ensure balanced learning and reduce bias toward the majority class.

Real-Time Adaptability – The system can integrate continuous data from EHRs and wearable devices for dynamic and proactive stroke risk monitoring.

IV. PROPOSED METHODOLOGY

The proposed methodology focuses on developing a robust machine learning pipeline for stroke prediction using clinical and demographic data. The workflow begins with data acquisition from publicly available healthcare datasets, followed by preprocessing steps including handling missing values, feature encoding, and normalization. Given the inherent class imbalance in stroke datasets, oversampling techniques such as SMOTE (Synthetic Minority Over-sampling Technique) are applied to ensure balanced learning. Multiple supervised ML algorithms—Logistic Regression, Random Forest, SVM, Gradient Boosting, and XGBoost—are trained and validated. Feature selection methods, including

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correlation analysis and recursive feature elimination, are used to identify the most significant predictors. Model performance is assessed using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC to ensure a comprehensive evaluation. The methodology emphasizes not only predictive accuracy but also interpretability, as explainability is critical in clinical adoption.

V. EXPERIMENTAL SETUP

The experimental setup involves the use of a publicly available stroke prediction dataset containing patient attributes such as age, gender, hypertension, heart disease, glucose levels, body mass index (BMI), smoking status, and work type. The dataset is split into training and testing sets with an 80:20 ratio. Data preprocessing includes normalization of continuous variables and one-hot encoding for categorical variables. To address class imbalance, SMOTE is applied before training. All models are implemented in Python using Scikit-learn and XGBoost libraries. Hyperparameter tuning is conducted through grid search and five-fold cross-validation to optimize performance. Evaluation metrics are computed on the testing set to compare models. The experiments were conducted on a standard computing environment with an Intel Core i7 processor and 16 GB RAM, ensuring reproducibility without specialized hardware.

VI. RESULTS AND DISCUSSION

The experimental results reveal that ensemble learning models outperform traditional classifiers in stroke prediction. Random Forest achieved an accuracy of 92% with a recall of 85%, making it particularly effective in identifying high-risk patients. Gradient Boosting and XGBoost also demonstrated strong performance, with AUC-ROC values above 0.90, indicating excellent discriminatory ability. Logistic Regression, while interpretable, lagged behind in performance with an accuracy of 82%. SVM achieved reasonable accuracy but struggled with recall due to class imbalance. Importantly, feature importance analysis indicated that age, hypertension, heart disease, and BMI were among the most influential predictors, consistent with clinical findings. These results reinforce the potential of ML-driven tools to complement medical decision-making. However, challenges such as data quality, generalizability to diverse populations, and explainability remain areas for further research

VII. CONCLUSION

This study demonstrates that machine learning offers a powerful approach for predicting brain stroke risk using clinical and demographic data. Ensemble-based models such as Random Forest and Gradient Boosting consistently outperformed traditional classifiers, highlighting their suitability for handling complex interactions among risk factors. The findings underscore the promise of integrating ML-based decision-support systems into neurology practice, enabling proactive interventions and improved patient outcomes. Future work should focus on enhancing interpretability, expanding datasets to include diverse populations, and integrating real-time data streams from wearable devices for continuous monitoring. By combining clinical expertise with data-driven intelligence, stroke prediction can evolve from reactive treatment toward preventive healthcare.

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