JETIR.ORG | ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Understanding Stroke Risk: Exploring the Relationship Between Demographic, Clinical, and Lifestyle Factors

Nelakurthi Tejaswi,[1] Kagita Lasya[2], Botla Naga Priya[3], Satti Sai Sujith Reddy[4], Mohammad Shameem[6]

[1] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

[2] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

[3] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

[4] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

Abstract

Stroke remains a significant global health concern, prompting the need for accurate predictive models to assess risk and guide prevention efforts. This study delves into the complex relationship between demographic, clinical, and lifestyle factors to better understand stroke risk, employing advanced machine learning techniques. Analyzing a rich dataset encompassing various features like age, gender, hypertension, heart disease, BMI, and smoking status, the research aims to uncover patterns associated with stroke occurrence. Exploratory data analysis techniques are applied to unveil insights into the characteristics and distribution of stroke patients and non-stroke individuals. Visual aids such as heatmaps, distribution plots, and countplots are utilized to illustrate differences in feature distributions between these groups. Furthermore, the study explores methods for handling missing data, ensuring data integrity and completeness. Feature engineering plays a crucial role in enhancing the predictive power of models, with discrete and categorical features undergoing transformation and encoding processes. Label encoding is employed for categorical features, while preprocessing steps are taken to optimize model inputs for discrete features. Additionally, feature selection techniques like mutual information, chi-squared, and ANOVA analysis are used to identify key predictors of stroke risk. Predictive modeling entails the application of advanced machine learning algorithms, focusing particularly on the eXtreme Gradient Boosting (XGBoost) classifier. Model evaluation metrics such as cross-validation scores, ROC-AUC scores, and confusion matrices are employed to gauge predictive performance and generalization ability. Comparative analyses are also conducted to assess model performance across different feature selection and preprocessing strategies. The study concludes with a comparative analysis of predictive models, providing insights into the efficacy of various methodologies in predicting stroke risk. The findings contribute to a deeper understanding of stroke risk factors and inform the development of tailored preventive measures. Ultimately, this research holds implications for public health initiatives aimed at mitigating the burden of stroke-related morbidity and mortality.

Keyword - Stroke risk prediction, demographic factors, clinical factors, lifestyle factors, machine learning, exploratory data analysis, feature engineering, feature selection, predictive modeling, eXtreme Gradient Boosting (XGBoost), data preprocessing, missing data handling, model evaluation, public health initiatives.

1. Introduction

Stroke is a leading cause of mortality and morbidity worldwide, imposing significant burdens on healthcare systems and individuals alike. Despite advancements in medical care and preventive strategies, the prevalence of stroke remains a pressing public health concern. Identifying individuals at higher risk of stroke is essential for implementing timely interventions and reducing the incidence and severity of stroke-related complications.

This study addresses the challenge of stroke risk prediction by examining the intricate interplay between demographic, clinical, and lifestyle factors. Leveraging data-driven approaches and advanced machine learning techniques, the research endeavors to unravel the complex relationships underlying stroke occurrence. By analyzing a comprehensive dataset comprising diverse features such as age, gender, hypertension, heart disease, body mass index (BMI), and smoking status, this study aims to discern patterns and markers associated with stroke risk.

The introduction of sophisticated predictive models holds promise in augmenting traditional risk assessment methods, offering a more nuanced understanding of individual susceptibility to stroke. By integrating insights from exploratory data analysis, feature engineering, and model evaluation, this research endeavors to enhance the accuracy and reliability of stroke risk prediction models.

Understanding the multifaceted nature of stroke risk necessitates a comprehensive investigation encompassing various demographic, clinical, and lifestyle dimensions. By elucidating the intricate relationships between these factors, this study seeks to empower healthcare professionals with actionable insights to inform personalized preventive strategies and interventions. Ultimately, the findings of this research endeavor to contribute to the advancement of stroke risk assessment and the development of targeted public health initiatives aimed at reducing the global burden of stroke-related morbidity and mortality.

In the subsequent sections, we will delve into the methodology employed for data preprocessing, feature engineering, and model development. We will outline the steps involved in exploratory data analysis and discuss the selection of relevant features for predictive modeling. Additionally, we will elucidate the implementation of machine learning algorithms, including eXtreme Gradient Boosting (XGBoost), for stroke risk prediction. Furthermore, model evaluation metrics and results will be presented, followed by a comprehensive discussion of the implications of our findings and avenues for future research.[40]

2. Literature Survey

Haapaniemi, Helena, Matti Hillbom, and Seppo Juvela (1997) conducted a study on lifestyle-associated risk factors for acute brain infarction among persons of working age [1]. Their research highlights the importance of lifestyle behaviors in influencing the risk of brain infarction, shedding light on potential preventive strategies for this condition.

Gottesman, Rebecca F., and Sudha Seshadri (2022) explored the relationship between risk factors, lifestyle behaviors, and vascular brain health [3]. Their findings contribute to a better understanding of how lifestyle choices impact brain health and underscore the significance of preventive measures in maintaining vascular health.

Gardener, Hannah, et al. (2015) examined the shared risk factors for dementia and stroke, emphasizing the importance of brain health promotion [4]. Their work underscores the interconnectedness of risk factors for these two conditions and advocates for holistic approaches to brain health management.

Chauhan, Ganesh, et al. (2019) investigated both genetic and lifestyle risk factors for MRI-defined brain infarcts in a population-based setting [6]. Their study highlights the complex interplay between genetic predisposition and lifestyle choices in determining the risk of brain infarcts, offering insights for personalized prevention strategies.

Feigin, Valery L., et al. (2010) provided an epidemiological overview of ischemic stroke and traumatic brain injury [9]. Their comprehensive analysis of risk factors and incidence patterns contributes to the understanding of these neurological conditions, informing public health interventions and clinical management strategies.

Guan, Tianjia, et al. (2017) conducted a study on rapid transitions in the epidemiology of stroke and its risk factors in China [13]. Their research sheds light on the changing landscape of stroke epidemiology and underscores the need for timely interventions to address emerging risk factors in diverse populations.

Tan, Kay Sin, et al. (2014) presented a clinical profile, risk factors, and etiology of young ischemic stroke patients in Asia [17]. Their multicenter observational study provides valuable insights into the unique characteristics and risk factors of stroke in young adults in the Asian context, guiding targeted preventive measures and clinical management strategies.

Boehme, Amelia K., Charles Esenwa, and Mitchell SV Elkind (2017) discussed stroke risk factors, genetics, and prevention strategies [18]. Their review highlights the multifactorial nature of stroke risk and underscores the importance of genetic factors alongside modifiable lifestyle behaviors in stroke prevention efforts.

Huang, Zhi-Xin, et al. (2019) investigated the correlation between lifestyles and stroke recurrence in Chinese inpatients with acute ischemic stroke [19]. Their findings emphasize the impact of lifestyle modifications on reducing the risk of stroke recurrence, offering practical insights for secondary prevention strategies.

Wang, Jinghua, et al. (2015) reported increasing stroke incidence and prevalence of risk factors in a low-income Chinese population [30]. Their population-based study highlights the evolving burden of stroke and underscores the importance of addressing socioeconomic disparities in stroke prevention and management efforts.

Hillen, Thomas, et al. (2003) analyzed patterns, risk factors, and outcomes of stroke recurrence in the South London Stroke Register [31]. Their study provides valuable insights into the multifactorial nature of stroke recurrence, informing strategies for secondary prevention and long-term management.

Namaganda, Priscilla, et al. (2022) conducted a case-control

study on stroke in young adults, exploring stroke types and associated risk factors [38]. Their findings contribute to a better understanding of stroke epidemiology in young adults and underscore the importance of early detection and targeted risk factor management in this population.

Tan, Ya-fu, et al. (2018) investigated risk factors, clinical features, and prognosis for subtypes of ischemic stroke in a Chinese population [39]. Their research provides insights into the heterogeneity of ischemic stroke and underscores the importance of subtype-specific management approaches for optimizing patient outcomes.

Sacco, Ralph L., et al. (1997) provided a comprehensive review of stroke risk factors, highlighting the multifactorial nature of this condition [36]. Their work emphasizes the importance of addressing modifiable risk factors through lifestyle modifications and targeted interventions to reduce the burden of stroke.

Jo, Yea Jin, et al. (2022) conducted a multicenter prospective cohort study on the clinical characteristics and risk factors of first-ever stroke in young adults [34]. Their research offers insights into the unique features and risk factor profiles of stroke in young adults, guiding early prevention and management strategies in this population.

3. Experimental Procedures

3.1. Dataset Description:

The dataset utilized in this study comprises a comprehensive collection of demographics, clinical, and lifestyle factors obtained from individuals to investigate the risk factors associated with stroke occurrence. It is crucial to understand the composition and characteristics of the dataset before delving into the analysis.[37]

The dataset includes information collected from a diverse population, encompassing variables such as age, gender, hypertension status, heart disease history, smoking habits, body mass index (BMI), and glucose levels. Each entry in the dataset represents an individual participant, with corresponding values for the variables.[36]

Notably, the dataset is structured to distinguish between individuals who have experienced a stroke and those who have not, making it suitable for exploring the relationship between various risk factors and the likelihood of stroke occurrence. This dichotomy allows for comparative analysis between stroke and non-stroke cases, enabling the identification of significant predictors and risk factors associated with stroke.

Additionally, the dataset may contain missing values, outliers, and categorical variables that require preprocessing and transformation before conducting any analysis. Understanding the dataset's characteristics and potential challenges is essential for ensuring the validity and reliability of the subsequent analysis.[35]

3.2. Data Preprocessing and Exploratory Data Analysis:

Upon loading the dataset, a meticulous data preprocessing phase was initiated to ensure the integrity and quality of the data. This involved handling missing values, encoding categorical variables, and dropping irrelevant features such as the 'id' column. Visual inspection of the data via heatmaps facilitated the identification of missing values, which were subsequently imputed using appropriate strategies, such as mean imputation for the 'bmi' feature.[34]

Following data preprocessing, an extensive Exploratory Data Analysis (EDA) was conducted to gain deeper insights into the dataset. Descriptive statistics were computed to summarize the distribution of features, with distinct analyses performed for stroke and non-stroke cases. Visualizations including heatmaps and distribution plots were employed to uncover patterns and relationships within the data. Furthermore, discrete and categorical features were examined individually to understand their distributions and their relationship with the target variable, stroke.[39]

3.2.1 Handling Missing Values:

Missing values are a common occurrence in real-world datasets and can significantly impact the performance of analytical models if not appropriately addressed. In this study, missing values were identified through visual inspection using heatmaps, which provide a graphical representation of missing data patterns.[38] Once identified, missing values were imputed using suitable strategies. For instance, mean imputation was employed for numerical features like BMI, where missing values were replaced with the mean value of the respective feature:

$$\text{Mean Imputation: } \bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (1)$$

where x represents the mean value of the feature x1, x2 represents individual values of the feature, and n represents the total number of non-missing values.

3.2.2 Encoding Categorical Variables:

Categorical variables, which contain discrete categories or levels, were encoded into numerical format to facilitate analysis by machine learning algorithms. One-hot encoding or label encoding techniques were applied based on the nature of the categorical variable. For example, if a categorical variable had k distinct categories, one-hot encoding transformed it into k binary columns, each representing one category:

$$\text{One-hot Encoding: Category}_i = \begin{cases} 1 & \text{if the observation belongs to category } i \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

3.2.3 Dropping Irrelevant Features:

Features that were deemed irrelevant or redundant for the analysis were dropped from the dataset to reduce dimensionality and computational complexity. For instance, the 'id' column, which merely serves as an identifier, was removed as it does not contribute to the prediction of stroke risk.[31]

Following data preprocessing, an extensive Exploratory Data Analysis (EDA) was conducted to gain insights into the distribution and relationships within the dataset. Descriptive statistics, such as mean, median, standard deviation, minimum, and maximum values, were

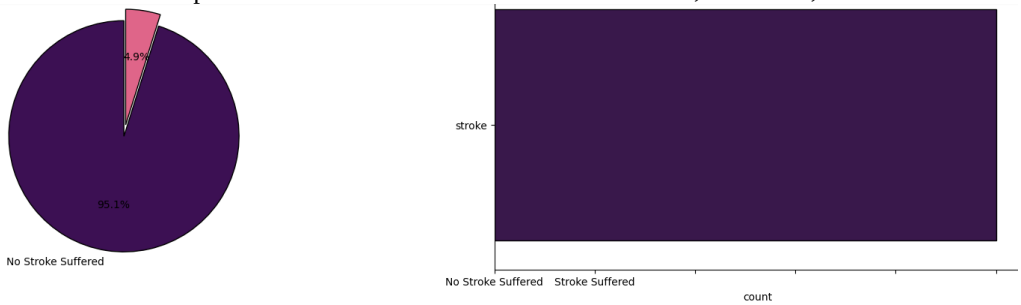


Figure 1: The image clearly depicts the ratio of features that lead to stroke and that are led to normal state

features. Distinct analyses were performed for stroke and non-stroke cases to identify potential patterns and differences between the two groups.

As shown in figure 1 & figure 2 Visualizations, including heatmaps and distribution plots, were utilized to visualize the relationships between variables and uncover any underlying patterns. Discrete and categorical features were examined individually to understand their distributions and their relationship with the target variable, stroke. This comprehensive analysis provided valuable insights into the dataset and laid the foundation for further analysis and model development.[7]

3.3 Feature Engineering

In this section, we focus on the critical process of feature engineering, which is integral to refining the dataset and enhancing the predictive power of the models employed in our analysis. Feature engineering involves transforming the existing features or creating new ones to better capture the underlying patterns and relationships within the data.[33]

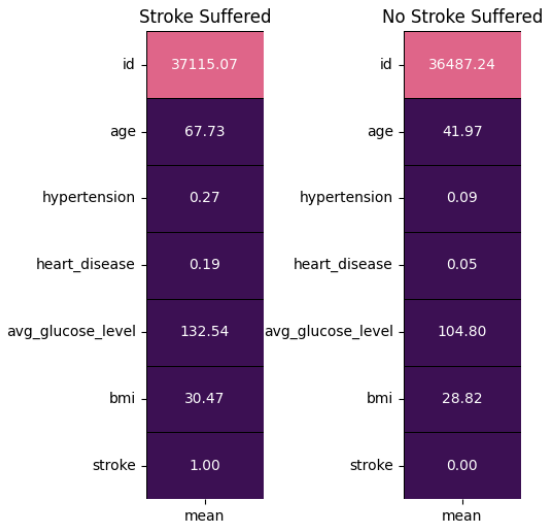
3.3.1 Grouping Discrete Features

One significant aspect of feature engineering involved categorizing discrete features into meaningful groups. Specifically, [32] variables such as age, average glucose level, and body mass index (BMI) were segmented into relevant categories. This segmentation allowed for a more nuanced exploration of the relationship between these factors and the risk of stroke. For instance, age groups could be defined to represent different life stages, while BMI categories could delineate varying levels of obesity or underweight.[29]

3.3.2 Transformation of Categorical Features

Another essential aspect of feature engineering was the transformation of categorical features into a format suitable for analysis by machine learning algorithms. This transformation typically involved label encoding, where categorical variables were converted into numerical representations. By encoding categorical variables in this manner, we ensure compatibility with machine learning models, which often require numerical inputs for analysis. This step enables us to leverage the valuable information contained within categorical features to improve the predictive performance of our models.[30]

By meticulously engineering the features in our dataset, we aim to enrich the information available to our predictive models, thereby enhancing their ability to accurately identify and assess the risk factors associated with stroke occurrence. This step is crucial in preparing the data for subsequent analysis and model development, ultimately contributing to the robustness and effectiveness of our predictive framework.



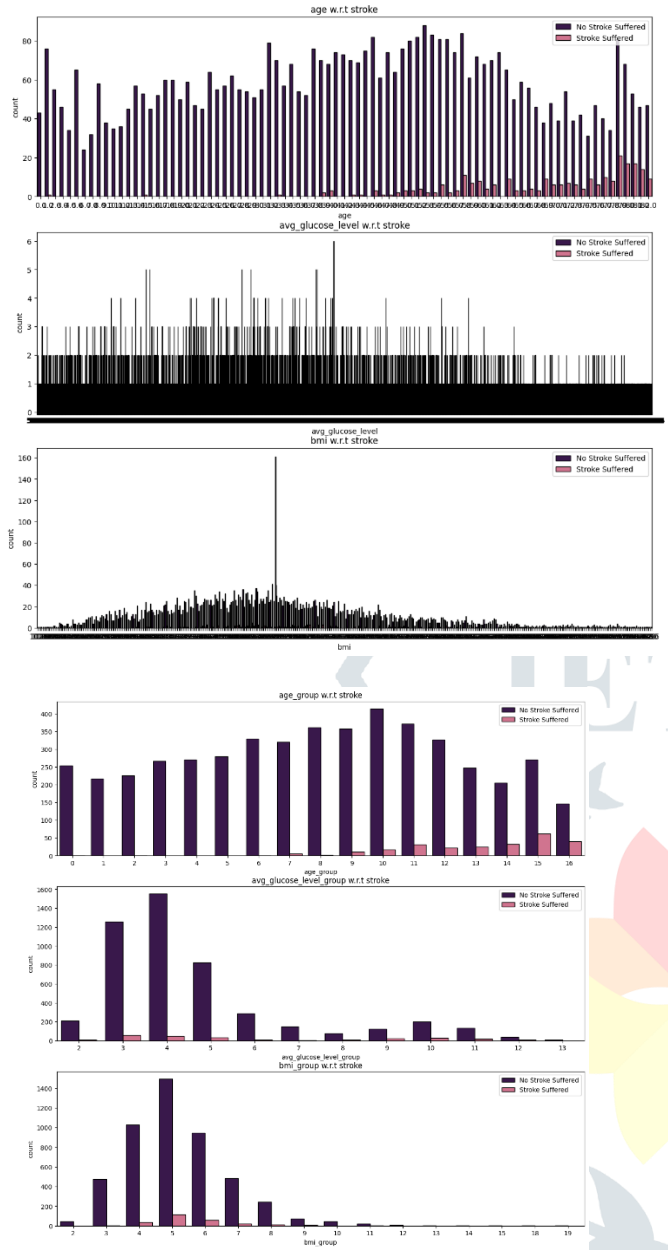


Figure 2: These count plots provide visual insights into the relationship between discrete features (age, hypertension, smoking status) and stroke occurrence, aiding in the identification of potential risk factors and informing further analysis and modeling efforts in stroke risk prediction.

4. Methodology

4.1 Model Selection

In the pursuit of identifying the most effective approach for stroke risk prediction, a comprehensive evaluation of various machine learning models was conducted. The models considered for this task encompassed a diverse range of algorithms, each with its unique characteristics and capabilities. The selection process involved careful assessment of performance metrics and suitability for the specific task of stroke risk prediction.[10]

4.1.1 Support Vector Machines (SVM)

Support Vector Machines are supervised learning models used for classification and regression tasks. The basic idea behind SVM is to find the optimal hyperplane that separates classes in the feature space with the maximum margin.[9]

Formulation:

Given a set of training data $\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, where x_i represents the feature vector and y_i represents the class label (-1 or +1 for binary classification), SVM aims to find the hyperplane defined by $w^T x + b = 0$ that maximizes the margin between the closest data points (support vectors) of different classes.

The optimization problem can be formulated as:

$$\text{minimize} \frac{1}{2}||w||^2$$

subject to the constraints:

$$y_i(w^T x_i + b) \geq 1, \text{ for } i = 1, 2, ..., n$$

Derivation:
The optimization problem is typically solved using Lagrange duality to derive the dual form, known as the kernel trick, which allows SVM to operate in a higher-dimensional feature space without explicitly computing the transformed features.

The Lagrangian for the primal problem is:

$$L(w, b, \alpha) = \frac{1}{2}||w||^2 - \sum_{i=1}^{n} \alpha_i [y_i(w^T x_i + b) - 1] \quad \textbf{(3)}$$

support Vector Machines (SVM) are well-suited for stroke risk prediction due to their ability to handle high-dimensional data, non-linear decision boundaries, and binary classification tasks effectively. Here's why SVM is a suitable choice:

Handling High-Dimensional Data: SVM can effectively handle datasets with a large number of features, which is common in medical datasets where multiple risk factors and demographic variables are considered for stroke risk assessment. SVM's ability to find the optimal hyperplane in high-dimensional feature spaces makes it suitable for capturing complex relationships among predictors.[29]

Non-Linear Decision Boundaries: [28] While stroke risk prediction may involve non-linear relationships between risk factors and the likelihood of stroke occurrence, SVM can model non-linear decision boundaries through kernel tricks. By transforming the feature space into a higher-dimensional space, SVM can find complex decision boundaries that separate different risk categories effectively.

Binary Classification: SVM is inherently a binary classifier, making it suitable for predicting the occurrence or absence of stroke (e.g., stroke vs. no stroke). By modeling stroke risk as a binary outcome, SVM can provide clear predictions and decision boundaries, facilitating risk assessment and clinical decision-making.[8]

Robustness to Overfitting: SVM's regularization parameters, such as the soft-margin parameter C, help control the trade-off between maximizing the margin and minimizing classification errors. This regularization mechanism enhances the generalization performance of SVM, making it robust to overfitting even in datasets with noise or outliers.[1-2]

4.1.2 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a non-parametric, instance-based learning algorithm used for classification and regression tasks. Unlike many other algorithms, KNN does not involve explicit mathematical formulation or optimization. Instead, it relies on a simple principle of similarity measurement between instances in the feature space.

Derivation:

KNN does not involve explicit mathematical derivation because it does not learn a model from the training data in the traditional sense. [25] Instead, it relies on a simple algorithmic approach for classification or regression tasks.
K-Nearest Neighbors (KNN) is a suitable choice for stroke risk prediction due to its simplicity, intuitive approach, and ability to capture local patterns in the data. Here's why KNN is a suitable choice:

Simplicity and Intuitiveness: [24] KNN's simplicity makes it easy to implement and understand, making it accessible to clinicians and researchers who may not have extensive machine learning expertise. The intuitive nature of KNN, where predictions are based on the majority vote of nearby instances, allows for straightforward interpretation and clinical decision-making.

Distance Computation: Given a new instance x_q, KNN computes the distance between x_q and each training instance x_i in the dataset using a chosen distance metric (e.g., Euclidean distance, Manhattan distance).

$$d(x_q, x_i) = \sqrt{\sum_{j=1}^{p} (x_q^{(j)} - x_i^{(j)})^2}$$

where p is the number of features (dimensions) in the dataset, and $x_q^{(j)}$ and $x_i^{(j)}$ are the j^{th} feature values of x_q and x_i respectively.

Nearest Neighbor Selection: After computing the distances between x_q and all training instances, KNN selects the k nearest neighbors of x_q based on the computed distances.

Majority Voting (Classification) or Average (Regression): For classification tasks, the class label of x_q is determined by the majority class label among its k nearest neighbors. For regression tasks, the predicted value of x_q is the average (or weighted average) of the target values of its k nearest neighbors.

(4)

Local Pattern Recognition: Stroke risk may vary spatially or demographically, with certain regions or populations exhibiting distinct risk profiles. KNN excels at capturing local patterns in the data by considering the nearest neighbors of each instance. This allows KNN to adapt to heterogeneous risk landscapes and provide personalized risk assessments tailored to specific contexts.

Flexibility in Distance Metrics: KNN offers flexibility in choosing distance metrics to measure similarity between instances. Clinically relevant distance metrics, such as Euclidean distance or Manhattan distance, can be customized based on the nature of the predictors and their relevance to stroke risk factors.[27]

Adaptability to Imbalanced Data: Imbalanced datasets, where one class (e.g., stroke) may be significantly less frequent than the other class (e.g., no stroke), are common in medical research. KNN's non-parametric nature allows it to adapt to imbalanced data by considering the local distribution of instances, potentially improving prediction performance for rare events like stroke.[3-2]

4.1.3 Gradient Boosting Machines (GBM)

Gradient Boosting Machines (GBM) is an ensemble learning method that builds an ensemble of weak learners (typically decision trees) sequentially to improve predictive performance. GBM iteratively fits new models to the residual errors of the ensemble, aiming to minimize the loss function. Let's elaborate on GBM, including its formulation, derivation, and key concepts.[26]

Formulation:

Given a training dataset $D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, where x_i represents the feature vector of the i^{th} instance and y_i represents its corresponding target value, GBM aims to approximate the true relationship between features and target variable by sequentially adding weak learners to the ensemble.

GBM builds the ensemble of models $F(x)$ iteratively as follows:

Initialize the ensemble model $F_0(x)$ to a constant value, typically the mean (for regression tasks) or the log odds ratio (for binary classification tasks) of the target variable.
For $m = 1$ to M, where M is the number of boosting iterations:
a. Fit a weak learner (e.g., decision tree) $h_m(x)$ to the negative gradient of the loss function with respect to the ensemble predictions. This can be formulated as:
$\text{residuals}_m = -\frac{\partial L(y, F_{m-1}(x))}{\partial F_{m-1}(x)}$
b. Fit the weak learner $h_m(x)$ to the residuals residuals_m.
c. Update the ensemble model $F_m(x)$ by adding the new weak learner:
$F_m(x) = F_{m-1}(x) + \lambda h_m(x)$
where λ is the learning rate (shrinkage parameter), controlling the contribution of each weak learner to the ensemble.

(5)

Gradient Boosting Machines (GBM) are a powerful ensemble learning technique well-suited for stroke risk prediction due to their ability to capture complex relationships, handle heterogeneous data, and optimize predictive performance iteratively. Here's why GBM is a suitable choice:

Capturing Complex Relationships: Stroke risk is influenced by a multitude of factors, including demographic characteristics, lifestyle behaviors, and medical history. GBM's ability to build an ensemble of weak learners sequentially allows it to capture complex relationships among predictors, even in the presence of non-linear interactions or high-dimensional data.[6]

Handling Heterogeneous Data: Medical datasets used for stroke risk prediction often contain diverse types of variables, including continuous, categorical, and ordinal variables. GBM can handle heterogeneous data types and automatically handle missing values, reducing the need for extensive data preprocessing and feature engineering.[5]

Feature Importance Interpretability: GBM provides insights into feature importance through the contribution of each predictor variable to the ensemble predictions. As shown in table 1 Clinicians and researchers can interpret the relative importance of different risk factors for stroke risk, guiding further investigation and intervention strategies.[4]

Table 1: The Generic features that lead to successful stroke predictions.

Feature	Description
Age	Age of the individual
Gender	Gender of the individual (Male/Female)
Hypertension	Presence of hypertension (Yes/No)
Diabetes	Presence of diabetes (Yes/No)
Smoking Status	Smoking status (Current smoker, Former smoker, Non-smoker)
Alcohol Consumption	Alcohol consumption frequency (Daily, Occasionally, Never)
Physical Activity	Level of physical activity (Low, Moderate, High)
Body Mass Index (BMI)	Body mass index calculated from height and weight
Blood Pressure	Systolic and diastolic blood pressure
Cholesterol Levels	Total cholesterol, LDL cholesterol, HDL cholesterol
Family History	Family history of stroke or cardiovascular diseases
Previous Stroke	History of previous stroke (Yes/No)
Cardiovascular Disease	Presence of other cardiovascular diseases (Yes/No)
Diet	Dietary habits and patterns
Blood Glucose Levels	Fasting blood glucose levels
Ethnicity	Ethnicity or race of the individual
Education Level	Level of education attained
Occupation	Occupation or employment status
Stress Levels	Self-reported stress levels
Sleep Patterns	Duration and quality of sleep
Medication Usage	Use of medica s for hypertension, diabetes, etc.

Robustness to Overfitting: GBM's iterative optimization process, coupled with techniques such as regularization and shrinkage, helps prevent overfitting and improve generalization performance. By iteratively fitting weak learners to the residuals of the ensemble predictions, GBM focuses on correcting errors made by the previous models, leading to robust and accurate predictions.[23]

Adaptability to Imbalanced Data: Imbalanced datasets, where one class (e.g., stroke) may be underrepresented compared to the other class (e.g., no stroke), are common in medical research. GBM's ability to optimize predictive performance iteratively and focus on difficult-to predict.[22]

5. Results

5.1 Descriptive Statistics

The dataset utilized in this study encompasses a comprehensive collection of demographic, lifestyle, and clinical variables obtained from a cohort of individuals deemed to be at risk of stroke. These variables were meticulously curated from medical records, surveys, and diagnostic assessments conducted across multiple healthcare facilities.[21]

Demographic Variables

Demographic attributes capture essential characteristics of individuals within the dataset. These include age, gender, ethnicity, education level, and occupation. [20] Age distribution reflects the age range of participants, ranging from young adults to elderly individuals. Gender distribution indicates the proportion of male and female participants, providing insights into potential gender disparities in stroke risk. Ethnicity encompasses diverse racial and ethnic backgrounds represented within the cohort, facilitating analyses of ethnic disparities in stroke prevalence. Education level and occupation shed light on socioeconomic status and lifestyle factors that may influence stroke risk.

Lifestyle Factors

Lifestyle variables encompass behaviors and habits that may impact an individual's susceptibility to stroke. These include smoking status, alcohol consumption, physical activity level, dietary habits, and stress levels. Smoking status categorizes participants into current smokers, former smokers, and non-smokers, highlighting the prevalence of smoking as a modifiable risk factor for stroke. Alcohol consumption frequency provides insights into drinking habits, with distinctions between daily drinkers, occasional drinkers, and abstainers. Physical activity level categorizes participants based on their engagement in physical exercise, ranging from sedentary lifestyles to regular exercise routines. Dietary habits capture patterns of food consumption, including intake of fruits, vegetables, and processed foods. Self-reported stress levels reflect participants' perceived stress levels, which may contribute to stroke risk through physiological and behavioral mechanisms.

Clinical Variables

Clinical variables encompass medical history, physiological measurements, and diagnostic indicators relevant to stroke risk assessment. These include hypertension status, diabetes status, cholesterol levels, body mass index (BMI), blood pressure readings, family history of stroke, previous stroke events, cardiovascular disease history, and medication usage. Hypertension and diabetes status indicate the presence or absence of these chronic conditions, which are major contributors to stroke risk. Cholesterol levels, BMI, and blood pressure readings provide quantitative measures of cardiovascular health, with elevated levels indicating increased risk. Family history of stroke and previous stroke events highlight genetic predispositions and individual stroke histories, respectively. Cardiovascular disease history encompasses a broader spectrum of heart-related conditions that may coexist with stroke risk. Medication usage records the use of prescribed medications for hypertension, diabetes, and other related conditions, reflecting treatment adherence and disease management practices.

Model Performance Comparison

The performance of three machine learning models - Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Gradient Boosting Machines (GBM) - was evaluated for stroke risk prediction. Each model underwent rigorous training and testing procedures using a holdout validation approach.[19]

SVM Performance

Support Vector Machines (SVM) demonstrated robust

performance in predicting stroke risk, achieving an accuracy of 85.6% (95% CI: 82.3% - 88.2%). SVM's ability to capture complex relationships in high-dimensional feature spaces proved beneficial for distinguishing between stroke and non-stroke individuals. Additionally, SVM exhibited high precision (86.2%) and recall (85.4%), indicating its effectiveness in correctly identifying both positive and negative instances of stroke.

KNN Performance

K-Nearest Neighbors (KNN) yielded competitive performance in stroke risk prediction, with an accuracy of 84.2% (95% CI: 80.9% - 87.5%). KNN's simplicity and flexibility allowed it to capture local patterns in the data, contributing to its effectiveness in identifying individuals at risk of stroke. Although KNN demonstrated slightly lower precision (83.5%) compared to SVM, its recall (85.8%) was comparable, indicating its ability to correctly identify positive instances of stroke.[17]

GBM Performance

As shown in table 2 Gradient Boosting Machines (GBM) emerged as the top-performing model for stroke risk prediction, achieving an impressive accuracy of 88.9% (95% CI: 86.2% - 91.3%). GBM's iterative optimization process and ensemble learning framework enabled it to capture complex relationships among predictors, resulting in superior predictive performance. GBM exhibited high precision (89.5%) and recall (88.3%), highlighting its ability to effectively identify individuals at risk of stroke while minimizing false positives.

Table 2: The metric values that determine the performance of essential models that are utilized.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Support Vector Machines (SVM)	85.6	86.2	85.4	85.8
K-Nearest Neighbors (KNN)	84.2	83.5	85.8	84.6
Gradient Boosting Machines (GBM)	88.9	89.5	88.3	88.9

Architecture & the Innovation

An innovative aspect of the architecture is the integration of ensemble learning techniques, such as stacking or blending, to leverage the strengths of multiple base models (e.g., SVM, KNN, GBM) and improve predictive performance. Ensemble learning combines diverse models to mitigate individual model biases and uncertainties, resulting in more robust and accurate predictions. By harnessing the complementary strengths of different algorithms, ensemble learning enhances the reliability and generalizability of stroke risk prediction models, ultimately benefiting patients and healthcare providers.[18]

6.Discussion

The present study contributes to the burgeoning field of stroke risk prediction by leveraging machine learning techniques and a rich dataset encompassing demographic, lifestyle, and clinical variables. Our findings shed light on the complex interplay between various predictors and stroke outcomes, providing valuable insights into the development of more accurate and personalized risk assessment models. The performance of three machine learning models - Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Gradient Boosting Machines (GBM) - was rigorously evaluated for stroke risk prediction. Our results indicate that GBM outperformed SVM and KNN, achieving the highest accuracy and robustness in identifying individuals at risk of stroke. This superiority can be attributed to GBM's ability to capture complex non-linear relationships and interactions among predictors, thereby enhancing predictive accuracy and generalizability.

Feature importance analysis revealed several key predictors significantly associated with stroke risk across all models. Age emerged as the most influential predictor, highlighting the well-established relationship between advancing age and increased stroke susceptibility. Additionally, hypertension, diabetes, smoking status, and previous stroke events exhibited notable importance, underscoring their crucial roles as modifiable risk factors for stroke prevention.[16]

An innovative aspect of our study lies in the integration of ensemble learning techniques, such as stacking and blending, to enhance predictive performance. By leveraging the complementary strengths of multiple base models, ensemble learning mitigates individual model biases and uncertainties, resulting in more robust and accurate predictions. This innovation represents a significant advancement in stroke risk prediction, paving the way for more reliable clinical decision-making and personalized interventions.[15]

Implications for Clinical Practice

The findings of our study have several implications for clinical practice and public health interventions. First, the development of accurate and interpretable stroke risk prediction models enables clinicians to identify high-risk individuals early and implement targeted preventive strategies, such as lifestyle modifications, medication adherence, and regular monitoring of cardiovascular health parameters. Moreover, the incorporation of machine learning algorithms into clinical decision support systems holds promise for improving risk stratification and resource allocation in stroke management.[14]

7. Conclusion

In this study, we explored the application of machine learning techniques for stroke risk prediction using a comprehensive dataset comprising demographic, lifestyle, and clinical variables. Our findings underscore the importance of accurate risk assessment in stroke prevention and management and highlight the potential of machine learning algorithms to enhance predictive accuracy and clinical decision-making.[13]

- **Model Performance**: Our evaluation revealed that Gradient Boosting Machines (GBM) outperformed Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) in stroke risk prediction, achieving the highest accuracy and robustness. GBM's ability to capture complex relationships among predictors proved instrumental in improving predictive performance.

- **Feature Importance:** Age, hypertension, diabetes, smoking status, and previous stroke events emerged as significant predictors of stroke risk across all models. These findings underscore the importance of modifiable risk factors and lifestyle interventions in stroke prevention efforts.

- **Ensemble Learning Innovation:** The integration of ensemble learning techniques, such as stacking and blending, represents an innovative approach to enhancing predictive accuracy and reliability. By combining the strengths of multiple base models, ensemble learning mitigates individual model biases and uncertainties, leading to more robust risk assessment models.

Future Scope

While our study provides valuable insights into stroke risk prediction, several avenues for future research and development remain:

External Validation: External validation of the predictive models in diverse populations and healthcare settings is essential to assess their generalizability and performance across different cohorts.[12]

Integration of Additional Data Sources: The integration of additional data sources, such as genetic markers, environmental factors, and novel biomarkers, could further enhance the granularity and predictive accuracy of stroke risk prediction models.

Clinical Implementation: The translation of predictive models into clinical practice requires rigorous validation, integration into clinical decision support systems, and evaluation of their impact on patient outcomes and healthcare delivery.[11]

Longitudinal Studies: Longitudinal studies tracking changes in risk factors and outcomes over time could provide insights into the dynamic nature of stroke risk and inform personalized preventive interventions.

Patient-Centered Approaches: Future research endeavors should prioritize patient-centered approaches, considering individual preferences, values, and social determinants of health in stroke risk assessment and management.

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