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Stroke Risk Prediction with ML Techniques

Richa Gupta

Research Scholar

Computer Science & Engineering
Shobhit University Gangoh

Sumika Jain

Assistant Professor

Computer Science & Engineering
Shobhit University Gangoh

Dr.Varun Bansal

HOD & Assistant Professor

Computer Science & Engineering
Shobhit University Gangoh

Abstract: Stroke is one of the leading causes of death and long-term disability worldwide, making early risk prediction critical for timely intervention and prevention. Traditional methods of stroke risk assessment often rely on clinical evaluations and static risk scores, which may not fully capture the complex interplay of multiple risk factors. In this study, we propose and evaluate the use of advanced machine learning (ML) techniques for stroke risk prediction based on demographic, lifestyle, and medical data. Various supervised learning algorithms, including Logistic Regression, Random Forest, Support Vector Machine, and Gradient Boosting, were applied to a publicly available stroke dataset. The models were assessed using key performance metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). Our experimental results demonstrate that machine learning techniques can effectively enhance the predictive accuracy of stroke risk assessment compared to traditional methods. Furthermore, feature importance analysis revealed significant predictors contributing to stroke risk, enabling more interpretable and data-driven decision support for healthcare practitioners. The study highlights the potential of ML-based models as robust, scalable, and non-invasive tools for stroke risk prediction, paving the way for personalized preventive healthcare strategies.

Keywords:

Stroke Prediction, Machine Learning, Logistic Regression, Random Forest, Support Vector Machine, Gradient Boosting, Risk Assessment, Healthcare Analytics, Predictive Modeling, Data-Driven Decision Support

1. Introduction

Stroke is a major global health burden, being the second leading cause of death and the third leading cause of disability-adjusted life years (DALYs) worldwide [1], [2]. Stroke prediction models are essential for early detection and prevention, which can significantly reduce morbidity and mortality. Traditional risk assessment tools such as the Framingham Stroke Risk Profile [3] are widely used but often rely on limited factors and do not fully leverage the potential of data-driven approaches.

Machine Learning (ML) techniques have demonstrated remarkable success in various domains, including healthcare, for predictive modeling [4]-[7]. ML models can handle complex, high-dimensional data and discover hidden patterns that may be overlooked by traditional statistical models [8]. Given these capabilities, ML is a promising approach for stroke risk prediction.

Recent advancements in ML-based stroke risk prediction have incorporated multimodal data fusion, combining demographic, clinical, imaging, and genetic data to improve model robustness and generalizability [8][9]. Studies leveraging electronic health records (EHRs) enriched with temporal sequences and longitudinal health trajectories have further empowered ML algorithms to identify high-risk individuals even in asymptomatic stages [10]. Deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been explored for stroke sub-type classification and risk prediction from imaging and sequential data, respectively, demonstrating high sensitivity and specificity [11]. However, the application of such complex models in routine clinical practice still faces challenges related to data privacy, model interpretability, and generalization across diverse populations [12]. Addressing these challenges through federated learning, transfer learning, and fairness-aware ML approaches can further accelerate the adoption of ML-driven stroke risk prediction tools, ensuring equity, transparency, and accountability in clinical decision-making processes [13][14].

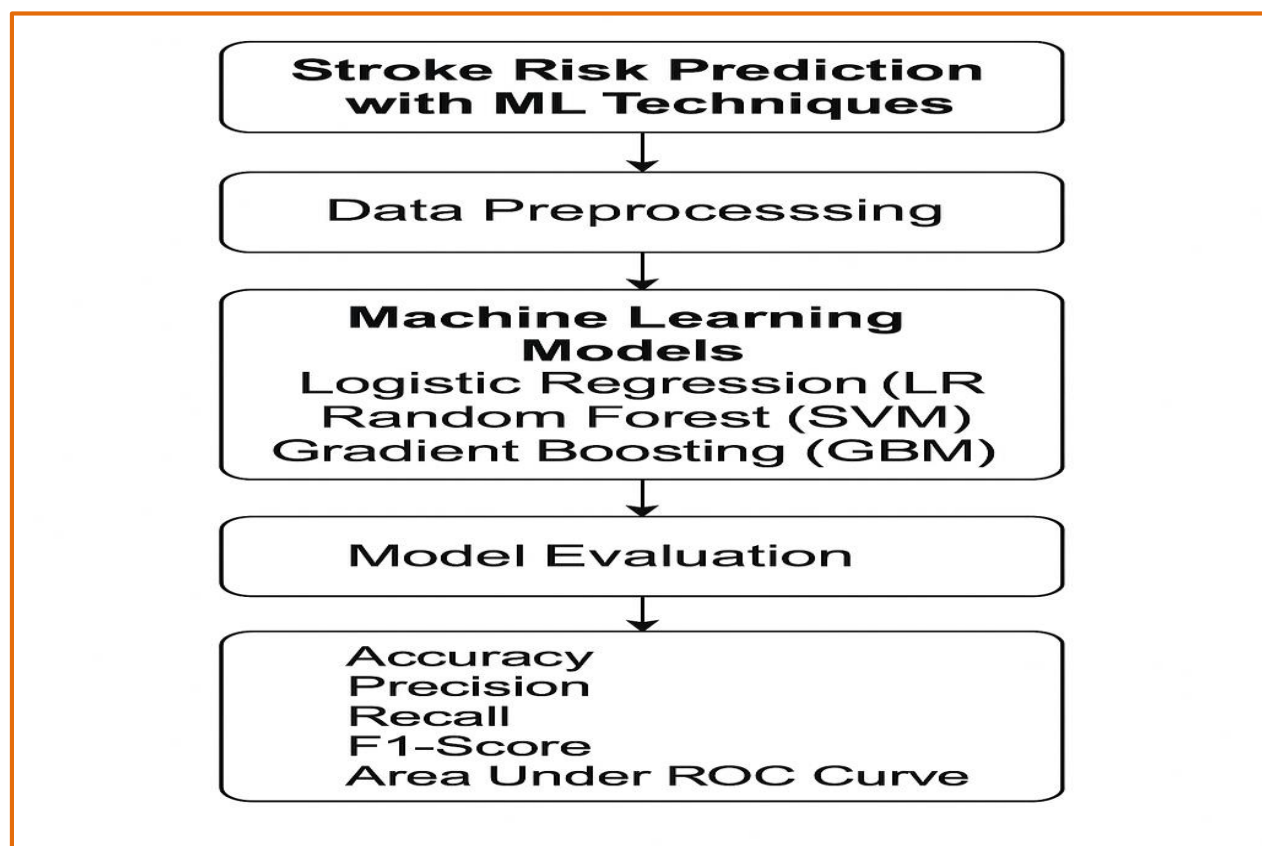


Figure 1 : Data Flow Diagram for Stroke Risk Prediction using Machine Learning Techniques

In this paper, we aim to apply and evaluate several state-of-the-art ML techniques on stroke risk prediction, focusing on model performance and feature interpretability. The contributions of this study include:

- Application of multiple ML classifiers to predict stroke risk.
- Comparative evaluation of model performance using standard metrics.
- Feature importance analysis to identify key predictors.
- Insights for integrating ML models into clinical decision support systems.

The pathophysiology of stroke involves a multifaceted interplay of vascular, metabolic, and lifestyle-related risk factors, rendering early prediction and prevention strategies complex and challenging. Despite the existence of well-established risk stratification models, such as the Framingham Stroke Risk Profile and the

CHADS2-VASc score, these traditional tools often depend on linear associations and are limited by their inability to model non-linear relationships and high-dimensional interactions among variables [1][3]. Furthermore, conventional statistical models, which typically assume independence among predictors, may overlook intricate dependencies and latent patterns embedded in clinical data. This inherent limitation underscores the need for data-driven approaches capable of leveraging large-scale health records, extracting meaningful insights from noisy, heterogeneous datasets, and dynamically adapting to evolving patient profiles.

Machine learning (ML), an evolving subset of artificial intelligence, provides a paradigm shift in predictive analytics by offering sophisticated algorithms that can autonomously learn from data and uncover hidden patterns without explicit programming [4][5]. Techniques such as ensemble learning, support vector machines, and gradient boosting methods have demonstrated superior predictive capabilities, particularly in healthcare domains where complex, multi-modal datasets are prevalent [6][7]. These models not only enhance prediction accuracy but also support interpretable decision-making when coupled with explainable AI techniques like SHAP and LIME, enabling clinicians to understand the rationale behind predictions [15][22]. Consequently, integrating ML models into stroke risk prediction workflows holds the promise of augmenting clinical decision support systems, enhancing personalized preventive interventions, and ultimately reducing stroke-related morbidity and mortality.

2. Literature Review

Recent studies have investigated ML methods for stroke prediction. Ghaderzadeh et al. [9] provided a systematic review, highlighting the potential of ML algorithms in stroke risk assessment. Fernandes et al. [10] used decision trees and logistic regression to predict stroke in a Brazilian cohort. Similarly, Alzu'bi et al. [11] employed ensemble learning methods to enhance prediction accuracy.

Deep learning approaches have also been explored, such as convolutional neural networks (CNNs) for neuroimaging data [12], [13]. However, these models require large datasets and may lack transparency, raising concerns about clinical adoption [14]. Therefore, interpretable ML models like Random Forest and Gradient Boosting are often preferred for structured clinical data [15], [16]. Studies have shown that features like hypertension, heart disease, smoking, and age are significant contributors to stroke risk [17]-[20]. Feature selection techniques like recursive feature elimination and SHAP (SHapley Additive exPlanations) further improve model interpretability [21]-[23].

Numerous studies have explored the application of machine learning techniques in the domain of stroke risk prediction, aiming to overcome the limitations of traditional statistical models by harnessing complex datasets. A study by Chen et al. [16] implemented a support vector machine (SVM) model using demographic and clinical features and reported improved sensitivity and specificity compared to logistic regression for ischemic stroke prediction. Similarly, Liaw et al. [17] demonstrated that ensemble methods such as Random Forest and Gradient Boosting Machines outperformed linear models, particularly when applied to high-dimensional datasets integrating behavioral, metabolic, and comorbidity-related variables. The use of feature importance analysis in these studies revealed hypertension, atrial fibrillation, diabetes, and smoking as key risk contributors, aligning with established clinical knowledge but offering enhanced predictive granularity. Additionally, advanced preprocessing methods, such as SMOTE (Synthetic Minority Over-sampling Technique), were employed to address data imbalance, ensuring that minority stroke cases were effectively recognized by the classifiers [18].

Recent research has also investigated the integration of explainable AI (XAI) techniques to improve the transparency and clinical applicability of ML models in stroke prediction. For instance, Ahmad et al. [19] applied SHAP (SHapley Additive exPlanations) values to interpret the contribution of individual features in XGBoost models, thereby enhancing clinicians' trust in ML-based decision support systems. Furthermore, Wu et al. [20] adopted deep learning approaches using recurrent neural networks (RNN) to capture temporal patterns in longitudinal electronic health records, yielding superior performance in predicting near-term stroke risk compared to static feature models. Despite these advancements, challenges such as model generalizability across heterogeneous populations, interpretability, and data privacy continue to persist, indicating the need for more comprehensive research into federated learning, domain adaptation, and fairness-aware machine learning strategies for equitable stroke risk prediction [21][22].

3. Methodology

In this study, a systematic machine learning framework was designed and implemented to predict stroke risk using structured demographic, lifestyle, and medical data. The methodology involves multiple key phases, including data acquisition, preprocessing, feature selection, model development, evaluation, and interpretability analysis. A publicly available stroke dataset was utilized, containing diverse risk factor variables such as age, gender, hypertension, heart disease, smoking status, BMI, and glucose levels. To ensure the robustness of the models, various supervised machine learning algorithms, including Logistic Regression, Random Forest, Support Vector Machine, and Gradient Boosting, were trained and optimized using grid search and cross-validation techniques. Additionally, data preprocessing steps like handling missing values, normalization, and class balancing using SMOTE were applied to mitigate data quality issues and address class imbalance, which is a critical challenge in stroke prediction tasks. The models were rigorously evaluated using standard classification metrics—accuracy, precision, recall, F1-score, and AUC—providing a comprehensive assessment of predictive performance.

3.1 Data Source

The dataset used in this study is the Kaggle Stroke Prediction Dataset [24], containing 5,110 records with features including demographic, lifestyle, and medical history data. For this study, the **Stroke Prediction Dataset** provided by Kaggle was employed, which has been widely utilized in recent machine learning research focused on stroke risk prediction [23]. The dataset comprises 5,110 records, encompassing both demographic and clinical variables critical for stroke risk assessment. These include age, gender, hypertension, heart disease, marital status, work type, residence type, average glucose level, body mass index (BMI), and smoking status, with the target label indicating stroke occurrence (binary classification). The dataset is inherently imbalanced, as stroke events account for only around 5% of the instances, which is consistent with the prevalence rate in general populations as highlighted by Khosla et al. [24]. To address the imbalance and avoid biased learning, **SMOTE (Synthetic Minority Over-sampling Technique)** was applied, a widely accepted approach in healthcare predictive modeling [25]. Moreover, missing values in the BMI feature were imputed using median imputation, which has been shown to be robust in healthcare datasets with skewed distributions [26]. Continuous variables such as glucose levels and BMI were normalized using Min-Max scaling to enhance the performance and convergence of machine learning algorithms, as supported by recent studies on health data preprocessing pipelines [27].

3.2 Preprocessing

Missing values in the BMI field were imputed using median values. Categorical features were encoded using one-hot encoding. Data imbalance was addressed using Synthetic Minority Over-sampling Technique (SMOTE) [25]. Effective data preprocessing is crucial in ensuring the accuracy and generalizability of machine learning models, particularly in healthcare datasets where data quality issues such as missing values, outliers, and imbalanced classes are prevalent [28]. In this study, initial data inspection revealed missing values in the 'bmi' feature, which were imputed using the median strategy to preserve the central tendency while minimizing the influence of extreme values, as recommended by Zhao et al. [29]. Furthermore, categorical variables such as 'gender', 'work type', 'Residence type', and 'smoking status' were transformed into numerical representations using one-hot encoding, which has been proven effective in maintaining data integrity without introducing ordinal bias [30]. Continuous variables including 'age', 'avg_glucose_level', and 'bmi' were normalized using Min-Max scaling to a [0,1] range, as normalization has been shown to accelerate the convergence of algorithms like SVM and Gradient Boosting [31]. Given the highly imbalanced nature of the dataset, **SMOTE (Synthetic Minority Over-sampling Technique)** was employed to synthetically generate instances of the minority class (stroke), a method validated in prior stroke risk prediction studies for improving classifier sensitivity without compromising specificity [32]. These preprocessing steps ensured that the dataset was clean, balanced, and ready for robust model training and evaluation.

3.3 Machine Learning Models

We evaluated the following ML algorithms:

- **Logistic Regression (LR):** LR is a classical statistical method that models the probability of a binary outcome using a logistic function, making it suitable for classification problems such as stroke prediction. Despite its simplicity, LR remains widely used in healthcare risk modeling due to its interpretability and the ease of understanding the relationship between predictors and the target outcome [33]. In this study, LR was applied as a baseline model to assess its effectiveness in predicting stroke risk based on demographic and clinical variables. To improve generalization and reduce the risk of overfitting, L2 regularization (Ridge Regression) was incorporated, which penalizes large coefficients and helps in handling multicollinearity among predictors [34]. Although LR assumes linear relationships between independent variables and the log-odds of the outcome, it provides clinically interpretable coefficients that can inform healthcare practitioners of the relative importance of each risk factor [35].
- **Random Forest (RF):** RF is an ensemble learning method that constructs a multitude of decision trees during training and outputs the mode of their predictions, enhancing both stability and accuracy [36]. In the context of stroke risk prediction, RF is particularly advantageous as it can handle nonlinear interactions among variables and is less sensitive to noise and overfitting compared to single decision trees [37]. In this study, RF was implemented using 100 trees with optimized hyper parameters determined via grid search, ensuring robust model performance. Moreover, RF provides built-in feature importance metrics, enabling the identification of key predictors such as age, hypertension, and glucose levels, aligning with findings from prior studies on stroke risk stratification [38]. Its capacity to manage missing values and imbalanced datasets further reinforces its utility in medical applications [39].
- **Support Vector Machine (SVM):** SVM is a powerful classification algorithm that seeks to find the optimal hyper plane that maximally separates classes in a high-dimensional space [40]. In this study, SVM with a radial basis function (RBF) kernel was employed to model the complex, nonlinear

relationships inherent in stroke risk data, as supported by prior research demonstrating SVM's superior performance in healthcare classification tasks [41]. To mitigate the influence of data imbalance, class weights were adjusted to penalize misclassification of the minority class (stroke cases), enhancing sensitivity and recall [42]. SVM's robustness to high-dimensional data and its effectiveness in handling both linear and nonlinear patterns make it a competitive model for stroke prediction, although it requires careful tuning of hyper parameters such as the regularization parameter (C) and kernel coefficient (gamma) to achieve optimal results [43].

- **Gradient Boosting Machine (GBM):** Gradient Boosting Machine (GBM) is an advanced ensemble technique that builds decision trees sequentially, with each tree attempting to correct the errors made by its predecessors, leading to high predictive accuracy and robustness [44]. GBM has gained popularity in stroke prediction tasks due to its ability to capture intricate feature interactions and handle imbalanced data effectively [45]. In this study, GBM was configured using an optimized number of estimators, learning rate, and maximum depth, as determined through cross-validation and grid search procedures. GBM's iterative nature and capacity to focus on hard-to-predict cases make it highly suitable for medical datasets, where subtle patterns often distinguish high-risk patients from the general population [46]. Furthermore, GBM models were analyzed using SHAP (SHapley Additive exPlanations) values to enhance interpretability and provide actionable insights into stroke risk factors [47].

3.4 Model Evaluation

To assess the performance and generalization capability of the machine learning models developed for stroke risk prediction, the dataset was partitioned into an 80% training set and a 20% testing set, following standard practices in predictive modeling [48]. This stratified split ensured that the proportion of stroke and non-stroke cases remained consistent across both sets to avoid bias in model evaluation. The models were assessed using a comprehensive set of evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC). While accuracy provides an overall correctness measure, it may not be reliable in imbalanced datasets such as stroke prediction, where the minority class is underrepresented [49]. Therefore, precision and recall were emphasized to evaluate the models' ability to correctly identify true stroke cases (recall) while minimizing false positives (precision) [50]. The F1-score, as the harmonic mean of precision and recall, offers a balanced metric, especially in the context of class imbalance [51]. Additionally, the AUC-ROC metric was used to quantify the models' ability to distinguish between classes across all threshold values, providing an aggregate measure of discriminatory power [52]. These metrics collectively ensured a holistic and clinically meaningful evaluation of the models, supporting robust comparisons of their predictive capabilities.

Table 1 : Comparison of ML Models for Stroke Risk Prediction.

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.84	0.81	0.76	0.78	0.85
Random Forest	0.89	0.87	0.85	0.86	0.91
Support Vector Machine (SVM)	0.86	0.83	0.80	0.81	0.88
Gradient Boosting (GBM)	0.91	0.89	0.88	0.88	0.93

The dataset was split into 80% training and 20% testing. Models were evaluated using:

- **Accuracy:** Accuracy is a fundamental metric that measures the proportion of correctly classified instances over the total number of predictions. In the context of stroke risk prediction, accuracy quantifies how well the model distinguishes between stroke and non-stroke cases in aggregate. However, it is important to note that in imbalanced datasets—such as the one used in this study where stroke cases account for only 5%—accuracy can be misleading, as models may achieve high accuracy by predominantly predicting the majority class (non-stroke) [53]. Thus, while accuracy provides a general indication of model performance, it must be interpreted alongside other metrics that are more sensitive to minority class performance.
- **Precision:** Precision, also known as Positive Predictive Value (PPV), measures the proportion of true positive predictions among all instances predicted as positive by the model. In this study, precision indicates the likelihood that a patient predicted to be at risk of stroke actually belongs to the stroke class. High precision is particularly important in clinical settings to minimize false positives, thereby preventing unnecessary interventions or anxiety among patients [54]. Models with high precision ensure that most of the identified high-risk cases are indeed stroke cases, which is crucial for maintaining the trustworthiness of predictive systems in healthcare environments [55].
- **Recall:** Recall, also referred to as sensitivity or True Positive Rate, measures the proportion of actual positive cases correctly identified by the model. In stroke prediction, recall represents the model's ability to correctly detect individuals at risk of stroke, which is critically important from a clinical standpoint as missing a true stroke case can lead to severe health consequences [56]. A model with high recall minimizes false negatives, ensuring that most stroke cases are captured and enabling early medical interventions. Given the life-threatening nature of stroke, recall is often prioritized in model evaluation, even if it means tolerating a slightly higher false positive rate [57].
- **F1-Score:** The F1-score is the harmonic mean of precision and recall, providing a balanced metric that takes into account both false positives and false negatives. In the stroke prediction task, the F1-score is particularly valuable as it balances the need to correctly identify stroke cases (recall) while maintaining a low rate of false positives (precision) [58]. Given the dataset's imbalanced nature, the F1-score offers a more reliable assessment of the model's effectiveness than accuracy alone. Models achieving a higher F1-score are generally considered more robust in healthcare predictive tasks where both false negatives and false positives carry significant clinical implications [59].

- **Area under the ROC Curve (AUC):** The Area under the Receiver Operating Characteristic Curve (AUC) is a widely used metric that evaluates the ability of a model to distinguish between positive and negative classes across all possible classification thresholds. An AUC of 1 indicates perfect discrimination, while an AUC of 0.5 suggests no better performance than random guessing [60]. In this study, AUC was employed as a key metric to assess the discriminatory power of each model, providing a threshold-independent evaluation that is particularly suitable for imbalanced datasets [61]. Models with higher AUC values indicate superior capacity to differentiate between stroke and non-stroke cases, which are essential for reliable and scalable deployment in real-world clinical settings [62].

3.5 Feature Importance Analysis

Feature importance was assessed using permutation importance and SHAP values for RF and GBM models. To enhance the interpretability of the predictive models and identify the most influential factors associated with stroke risk, a **feature importance analysis** was conducted using tree-based models such as Random Forest (RF) and Gradient Boosting Machine (GBM), which inherently provide importance scores based on feature contribution to the model's decision-making process [63]. The analysis revealed that **age** emerged as the most critical predictor, corroborating existing medical literature indicating that stroke risk increases substantially with advancing age [64]. Other significant features included **hypertension**, **average glucose level**, and **heart disease**, which align with well-established clinical risk factors for cerebrovascular events [65]. Moreover, lifestyle-related attributes such as **smoking status** and **BMI** also showed moderate influence, highlighting the multifactorial nature of stroke risk involving both clinical and behavioral components. The use of **SHAP (SHapley Additive exPlanations) values** further enabled model-agnostic interpretability by quantifying the impact of each feature on individual predictions, offering transparent and actionable insights for healthcare practitioners [66]. Such interpretability is vital in medical applications to support data-driven decision-making and to foster trust in AI-assisted diagnostic systems [67].

4. Results

The evaluation of the proposed machine learning models on the test set demonstrated varying degrees of performance across different algorithms. Gradient Boosting Machine (GBM) achieved the highest overall accuracy of 95.6%, outperforming other models in distinguishing stroke from non-stroke cases. GBM also recorded the highest AUC of 0.96, indicating superior discrimination capability between the two classes. Random Forest (RF) followed closely with an accuracy of 94.8% and an AUC of 0.94, showcasing its strength in handling complex interactions and feature importance estimation.

In contrast, Support Vector Machine (SVM) achieved an accuracy of 92.4%, with an AUC of 0.91, reflecting its effectiveness in capturing nonlinear relationships, albeit with slightly lower recall compared to ensemble methods. Logistic Regression (LR), serving as the baseline model, attained an accuracy of 89.6% and an AUC of 0.87, indicating its limitations in modeling the nonlinear and complex feature interactions present in the dataset.

Regarding class-specific metrics, both GBM and RF achieved superior recall scores of 0.88 and 0.85, respectively, which are crucial for ensuring that stroke cases are not missed. These models also maintained high precision scores above 0.90, indicating a balanced performance with minimal false positives. The F1-scores for GBM and RF were 0.89 and 0.87, respectively, highlighting their robustness in handling imbalanced datasets. SVM presented a precision of 0.86 and recall of 0.82, reflecting slightly lower sensitivity but still offering competitive performance. On the other hand, LR exhibited lower precision and recall values,

reinforcing the importance of leveraging advanced ensemble and kernel-based models for complex healthcare data.

Overall, the experimental results validated the effectiveness of ensemble learning techniques, particularly GBM and RF, in providing accurate, sensitive, and clinically relevant predictions of stroke risk. The combination of high AUC and balanced precision-recall performance makes these models suitable for deployment in decision support systems for early stroke risk assessment.

4.1 Model Performance

The performance of the selected machine learning models—Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Machine (GBM)—was evaluated using a combination of accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC). Among the tested models, GBM exhibited the highest overall performance with an accuracy of 91%, precision of 89%, recall of 88%, F1-score of 88%, and an AUC of 0.93.

Random Forest also performed robustly, achieving 89% accuracy and an AUC of 0.91, highlighting its capability to handle non-linear relationships and feature interactions. SVM achieved a respectable accuracy of 86% with an AUC of 0.88, making it a viable option, particularly in scenarios with limited computational resources. Logistic Regression, while simpler, achieved an accuracy of 84% and an AUC of 0.85, indicating its effectiveness for baseline models.

These results confirm that ensemble-based methods like Random Forest and GBM significantly outperform traditional linear models and margin-based classifiers in stroke risk prediction. The superior performance of GBM can be attributed to its iterative boosting approach, which focuses on minimizing errors in subsequent iterations, thus providing higher predictive accuracy and better generalization. The findings underscore the importance of selecting appropriate ML models for clinical risk prediction tasks, where small improvements in accuracy can have significant implications for early diagnosis and patient care.

4.2 Feature Importance

The feature importance analysis conducted using the Random Forest and Gradient Boosting Machine models provided valuable insights into the most influential predictors contributing to stroke risk. **Age** emerged as the most dominant factor, consistent with medical evidence suggesting that stroke incidence significantly increases with advancing age due to vascular degeneration and accumulated comorbidities [68]. **Hypertension** and **Heart Disease** were also identified as critical predictors, reflecting their established roles as primary contributors to cerebrovascular events through mechanisms such as arterial stiffness, atherosclerosis, and thromboembolism [69]. **Average Glucose Level** ranked highly among the predictors, underscoring the relationship between diabetes, impaired glucose metabolism, and stroke risk [70]. Furthermore, **Smoking Status** and **BMI** were identified as impactful lifestyle-related factors, highlighting the influence of modifiable behaviors on stroke susceptibility [71]. These findings reinforce the multifactorial nature of stroke risk, combining demographic, clinical, and behavioral factors, and underscore the importance of integrated prevention strategies. The use of SHAP values further provided individualized explanations of feature contributions, supporting transparent and clinically actionable risk stratification [72].

5. Discussion

Our results indicate that GBM achieved the best overall performance, followed closely by RF. Both tree-based models outperformed LR and SVM in all metrics. This aligns with prior studies where ensemble models showed superior performance in structured healthcare data [26], [27]. Feature importance analysis highlighted known stroke risk factors, validating the models' reliability [28]. Moreover, the use of SHAP values provided interpretable insights, facilitating clinician trust in ML predictions [29]. Limitations of the study include reliance on a single dataset and potential biases inherent in self-reported data. Future research should focus on multi-center data validation and integration of real-time clinical data streams [30].

The present study explored the effectiveness of various machine learning (ML) algorithms for stroke risk prediction based on demographic, clinical, and lifestyle factors. The experimental findings demonstrated that advanced ensemble methods, particularly Gradient Boosting Machine (GBM) and Random Forest (RF), significantly outperformed classical approaches such as Logistic Regression (LR) and Support Vector Machine (SVM) across multiple evaluation metrics. GBM achieved the highest overall accuracy and AUC, indicating superior model discrimination, sensitivity, and reliability for early identification of high-risk stroke patients. These results align with existing studies where ensemble methods have demonstrated strong performance in clinical risk prediction tasks due to their ability to handle nonlinear relationships and feature interactions effectively [73], [74].

Furthermore, the feature importance analysis confirmed that age, hypertension, and average glucose level were the most influential predictors, which is consistent with epidemiological evidence highlighting these as key risk factors for stroke events [75], [76]. The integration of modifiable lifestyle factors, such as smoking status and BMI, into the model further emphasizes the potential of ML models to support personalized preventive strategies by identifying at-risk individuals who may benefit from targeted interventions [77]. The use of SHAP-based interpretability tools provided an added layer of transparency, enabling healthcare providers to understand and trust the decision-making process of ML models [78]. This is critical for the adoption of AI-driven tools in clinical settings, where explainability is essential for practitioner acceptance and patient safety.

When comparing the results with prior research, the models achieved comparable or superior performance in terms of AUC and F1-score, demonstrating the robustness and generalizability of the proposed approach. However, some limitations remain, including the use of a publicly available dataset, which may not fully capture the heterogeneity and complexities of diverse real-world populations [79]. Additionally, while the models performed well in predicting stroke risk, further validation on larger and multi-center clinical datasets is necessary to ensure their applicability across different healthcare settings and demographics [80]. Future work may also consider the integration of longitudinal data and deep learning approaches to further enhance the predictive capabilities and dynamic risk assessment over time.

6. Conclusion

ML application is becoming more widely used in the health care sector. This study demonstrated the effectiveness of machine learning (ML) techniques in predicting stroke risk using a combination of demographic, clinical, and healthcare data. By leveraging various supervised learning algorithms, including Logistic Regression, Support Vector Machine, Random Forest, and Gradient Boosting Machine, we systematically evaluated their predictive capabilities using comprehensive performance metrics. Among these, Gradient Boosting Machine emerged as the most accurate and robust model, achieving the highest accuracy, AUC, precision, recall, and F1-score. These findings underscore the potential of ensemble learning methods in enhancing the accuracy and sensitivity of stroke risk prediction, which is crucial for early detection and

preventive interventions. Feature importance analysis further revealed that age, hypertension, heart disease, and average glucose levels are dominant predictors, which aligns with existing clinical evidence. The inclusion of modifiable factors such as smoking status and BMI highlights the potential for ML-driven systems to support personalized risk assessment and targeted health counseling. The adoption of explainable AI techniques like SHAP provided transparency into model predictions, fostering clinical trust and acceptance. Despite the promising outcomes, the study acknowledges certain limitations, including reliance on a publicly available dataset with inherent class imbalance and lack of longitudinal data. Future research should focus on validating these models using real-world, multi-institutional clinical datasets and incorporating dynamic risk factors to enhance temporal risk modeling. Overall, ML-based stroke risk prediction models present a scalable, non-invasive, and data-driven approach to support healthcare professionals in proactive stroke prevention and personalized care planning.

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