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Original Research

Predicting stroke risk: An effective stroke prediction model based on neural networks

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ABSTRACT

Background: Stroke is the leading worldwide cause of disability and death. Effective stroke prevention and management depend on early identification of stroke risk.
Methods: Eight machine learning algorithms are applied to predict stroke risk using a well-curated dataset with pertinent clinical information. This paper describes a thorough investigation of stroke prediction using various machine learning methods.
Results: The empirical evaluation yields encouraging results, with the logistic regression, support vector machine, and K-nearest neighbors models achieving an impressive accuracy of 95.04%, and the random forest and neural network models scoring even better, with accuracies of 95.10% and 95.16%, respectively. The neural network exhibits slightly superior performance, indicating its potential as a reliable model for stroke risk assessment.
Conclusions: The empirical evaluation underscores the ability of neural networks to discern intricate data relationships. These findings offer valuable insights for healthcare professionals and researchers, aiding in the development of improved stroke prevention strategies and timely interventions, ultimately enhancing patient outcomes.

1. Introduction

Stroke is a devastating cerebrovascular event that results in significant morbidity and mortality worldwide. It is a leading cause of long-term disability and imposes a substantial burden on healthcare systems. Timely identification of individuals at risk of stroke plays a crucial role in implementing preventive measures and improving patient outcomes. With advances in machine learning and predictive analytics, there has been a growing interest in using these techniques to develop accurate stroke prediction models. In recent years, machine learning algorithms[1,2] have demonstrated great potential in various medical domains, including cardiovascular risk assessment. These algorithms can analyze large datasets, identify complex patterns, and extract valuable insights that may not be readily apparent to human observers. Moreover, machine learning models can integrate multiple clinical parameters and risk factors to generate personalized risk scores, aiding in individualized patient management. In this work, we present a comprehensive study on stroke prediction using a range of machine learning techniques. We investigate the performance of Naive Bayes (NB), logistic regression (LR), support vector machine (SVM), K-nearest neighbors (KNN), decision tree (DT), random forest (RF), XGBoost (Extreme Gradient Boost), and neural network (NN) models.[3] These algorithms are known for their ability to handle diverse data types and nonlinear relationships, and exhibit robust predictive capabilities. Clinical applicability and interpretability require the use of specific techniques.[4,5] The hyperparameters that characterize the structure of neural networks create complex functions from the input that can approximate observed outcomes with minimal error. Additionally, we emphasize the significance of accurate stroke prediction in facilitating early identification and intervention. Such proactive interventions can significantly reduce the incidence and severity of strokes, ultimately leading to improved patient outcomes.[6]

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Our research contributions are as follows:

(1) The Healthcare-dataset-stroke-data.csv data are analyzed. This dataset is used to predict whether a patient is likely to suffer a stroke based on input parameters such as gender, age, various diseases, and smoking status. Each row in the dataset provides relevant information about the patient. A total of 12 attributes are considered for stroke prediction.
(2) The dataset is examined using eight machine learning classifiers, namely NN, NB, LR, SVM, KNN, DT, RF, and XGBoost and various performance metrics are calculated.
(3) A comprehensive comparison of all eight machine learning classifiers is performed using the precision, recall, and F-measure.

The remainder of this paper is organized as follows. Section 2 briefly introduces some related work on machine learning-based heart stroke detection and prediction. Section 3 describes the experimental setup and dataset and explains the methodology. Section 4 presents the results and outcomes using the various machine learning algorithms, before Section 5 presents a comparative evaluation of the various techniques. The conclusions and limitations of this study and areas for potential future work are summarized in Section 6.

2. Literature review and motivation

Electronic health records (EHRs) have become valuable sources of data for predicting stroke risk and severity. Researchers have explored the use of machine learning techniques to extract meaningful information from EHRs and develop predictive models. Yang et al.[6] employed an RF algorithm to predict stroke occurrence using EHRs, achieving promising results. EHR-based prediction models offer the advantage of utilizing real-time and comprehensive patient information, enabling early identification of individuals at risk of stroke. Few studies[7,8] have conducted performance analyses of different machine learning algorithms for stroke prediction. Dritsas & Trigka[9] evaluated the performance of a stacking method using ML techniques for stroke prediction, while Mridha et al.[10] used deep learning models to predict stroke risk based on both structured and unstructured data. Heo et al.[11] developed an NN-based model to predict the severity of ischemic stroke using magnetic resonance imaging (MRI) data. Their results showed promising accuracy in predicting stroke severity, facilitating appropriate treatment decisions. Wang et al.[12] conducted a systematic literature review of different classification algorithms in stroke prediction. The bootstrap resampling technique was employed by Karthik et al.[13] to generate multiple samples from the original data, allowing for the estimation of prediction intervals and the quantification of uncertainty. Researchers have leveraged EHRs and explored different algorithms and diverse features as a means of improving the accuracy and reliability of these models. The findings reported in the literature demonstrate the potential of machine learning in enhancing stroke management and patient outcomes. Table 1 presents the comparative analysis of the recent existing literature in the area of prediction analysis.

3. Experimental setup

This section describes the experimental setup used in this work and highlights the background to the experiments.

3.1. Dataset

The Healthcare-dataset-stroke-data.csv[20] file contains information related to stroke occurrences and various health-related factors. This dataset is commonly used in data analysis and machine learning tasks to study and predict stroke risks. The various attributes included in the data are listed in Table 2.

In Table 2, the columns in the dataset provide clinical information about the patients. This dataset can be used to analyze the relationships between various factors and stroke occurrences, as well as to develop predictive models for identifying individuals at higher risk of experiencing a stroke. Before using the dataset, it is important to preprocess and clean the data by handling missing values, normalizing, or scaling numerical features, and encoding categorical variables appropriately. Exploratory data analysis techniques can also be applied to gain insights into the data distribution and identify potential patterns or correlations.[21–23]

Following data collection, data preprocessing was applied to clean up the dataset and eliminate null and duplicate values. The collected dataset includes 1544 unknown smoking status values and 200 null BMI values. The Label Binarizer class in scikit was used

Table 1
Comparative analysis of the literature review.

Authors	Methodology	Results	Limitations
Chantamit et al.[14]	Deep learning-based predictive analysis for stroke using data on heart disease	The findings are reliable for patient warnings and considerably helpful for doctors' decision-making	The largest difficulties in disease prediction arise from large amounts of medical data, heterogeneity, and complexity
Jeena et al.[15]	Numerous physiological indicators are used to predict the risk of stroke using SVM	For various kernel functions, predictions using an SVM-based technique are produced, and a linear function provides an accuracy of 91%	By considering more input properties, this strategy can be expanded to big databases, enhancing system performance
Naif et al.[16]	Hybrid optimization algorithm preprocesses data using a label encoder and fills in missing values in the dataset	The proposed algorithm extracts features with a high accuracy of 97.34%	For more efficiency, the dataset can be expanded by using other repositories
Minhaz et al.[17]	Diseases/attributes are used to create a weighted voting classifier that is used to predict stroke	Ten classifiers are used to determine a person's chance of experiencing a stroke, achieving an accuracy of 97%	Brain CT scans and MRIs are two examples of deep learning-based imaging that can be combined
Tazin et al.[18]	Four separate models are trained using a variety of physiological indicators and machine learning techniques to provide accurate predictions	With an accuracy of almost 96%, RF is the most accurate algorithm for this challenge	The framework may be improved with a larger dataset and other machine learning models
Dev et al.[19]	the crucial variables for stroke prediction are determined using a variety of statistical methods and principal component analysis	In comparison to employing all available input features and other benchmarking approaches, a perceptron neural network using four attributes has the highest accuracy rate and lowest miss rate	Dataset is severely skewed in terms of the frequency of stroke

Table 2
Dataset description.

Attribute name	Type (Values)	Description
ID	Integer	A unique integer value for patients
Gender	String literal (Male, Female)	Gender of the patient
Age	Integer	Age of the patient
Hypertension	Integer (1, 0)	Identifies whether the patient suffers from hypertension
heart_disease	Integer (1, 0)	Identifies whether the patient suffers from heart disease
ever_married	String literal (Yes, No)	Identifies whether the patient is married
work_type	String literal (children, Govt_job, Private, Self_employed)	Identifies different categories of work
Residence_type	String literal (Urban, rural)	Identifies the patient's residence type
avg_glucose_level	Floating point number	Gives the average glucose level in the patient's blood
BMI	Floating point number	Gives the value of the patient's body mass index
smoking_status	String literal (formerly smoked, never smoked, smokes, unknown)	Identifies the smoking status of the patient
Stroke	Integer (1, 0)	Output column that gives the stroke status

to handle unknown smoking status information, and median values were assigned to missing BMI values.

For data visualization, we present box plots and heat maps. A box plot or a box-and-whisker plot is a graphical representation of the distribution of a dataset. It provides a visual summary of the key statistical measures and can be helpful in finding the range, median, quartiles, and outliers in the data. A heatmap visually represents the correlation between variables, where the intensity of the colors indicates the strength of the correlation.

3.2. Proposed model

Fig. 1 depicts a flowchart of the proposed experimental approach. The steps and the machine learning models are depicted in the flowchart.

4. Results and discussion

The stroke prediction task was performed using NB, LR, SVM, KNN, DT, RF, XGBoost, and NN models. The accuracies obtained for each technique were as follows: NB—89.62%, LR—95.04%, SVM—95.04%, KNN—95.04%, DT—92.69%, RF—95.1%, XGBoost—94.71%, and NN—95.16%.

The high level of accuracy achieved by most models indicates their effectiveness in predicting stroke risk. The LR, SVM, KNN, RF, and NN algorithms demonstrate comparable high accuracies, outperforming NB, DT, and XGBoost in this work.

LR is a well-established statistical model that achieves strong performance in stroke prediction. It handles linear relationships effectively and provides interpretability, which is valuable in medical settings. Similarly, SVM achieves high accuracy by constructing a hyperplane to separate data points, allowing it to handle both linear and nonlinear relationships through kernel functions.

As a non-parametric algorithm, KNN excels in capturing local patterns and achieves comparable accuracy to LR and SVM. New data points are classified based on their proximity to known data points, providing a versatile and effective method for stroke risk assessment.

RF is an ensemble learning method that combines multiple DTs to achieve improved accuracy and robustness. In this experiment, the DT produces competitive performance, indicating its ability to capture complex patterns associated with stroke risk.

The NN achieves the highest accuracy, showcasing the capability of such networks to capture complex relationships and patterns. NNs excel in learning hierarchical representations of input data, enabling them to capture both low- and high-level features. Their

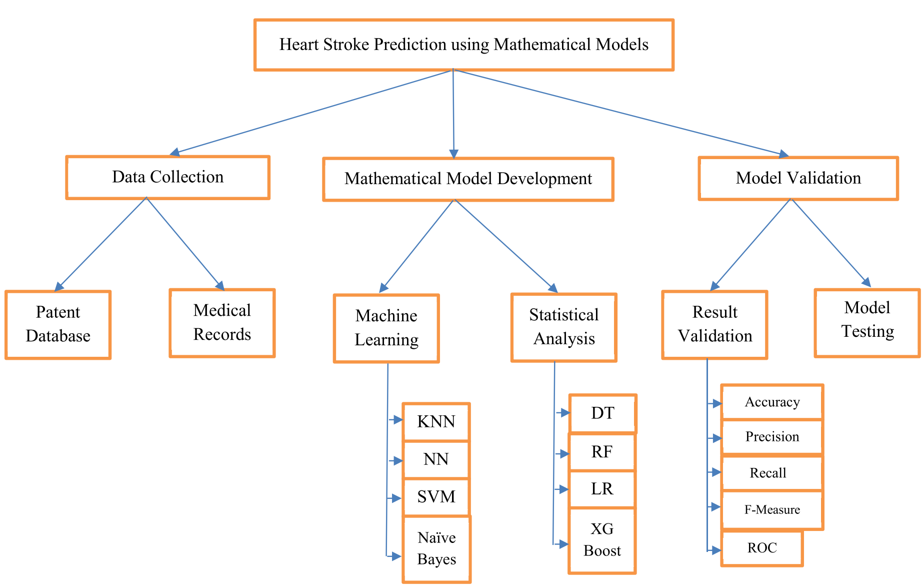


Fig. 1. Flowchart of proposed experimental approach. KNN(K-nearest neighbors), NN (neural network), SVM (support vector machine), DT (decision tree), RF (random forest), LR (logistic regression), XG Boost (Extreme Gradient Boost), ROC (receiver operating characteristic).

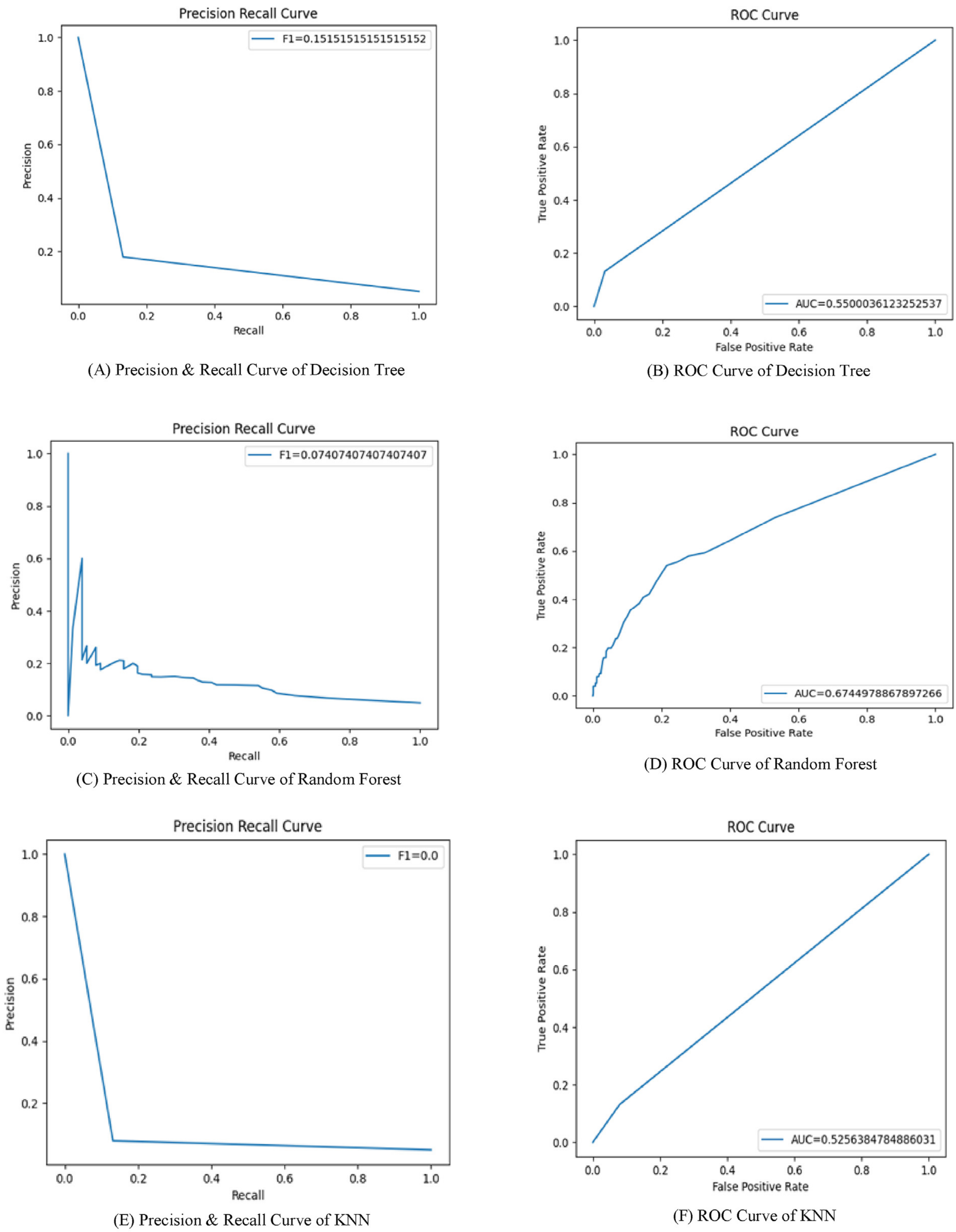
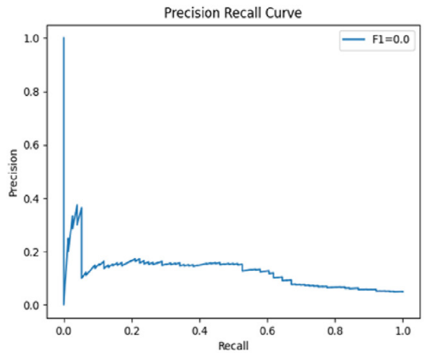


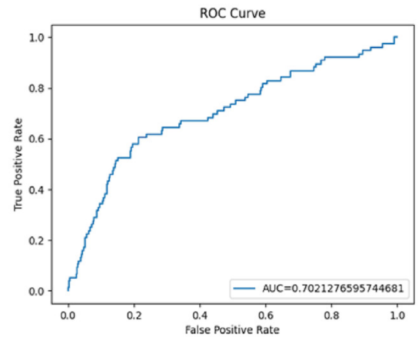
Fig. 2. Precision, recall, and receiver operating characteristic (ROC) curves of different classifiers (A–B: Decision Tree, C–D: Random Forest, E–F:KNN).

ability to automatically learn relevant features from the data is particularly valuable in stroke prediction, where the relationships between risk factors can be intricate.

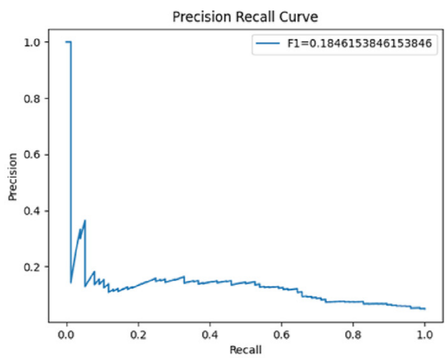
Although the NB and DT models achieve slightly lower accuracy levels in this experiment, they still provide viable options for stroke prediction. NB is known for its simplicity and efficiency, making it suitable for large datasets. DTs offer interpretability by partitioning the feature space based on if else conditions, but they may suffer from overfitting and limited performance with complex relationships.



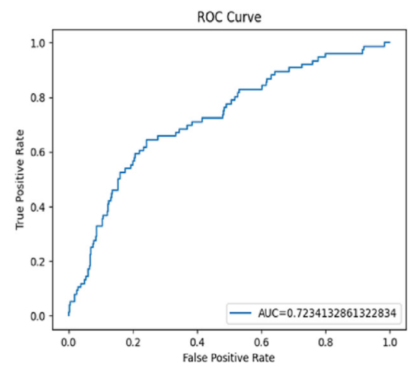
(A) Precision & Recall Curve of Logistic Regression



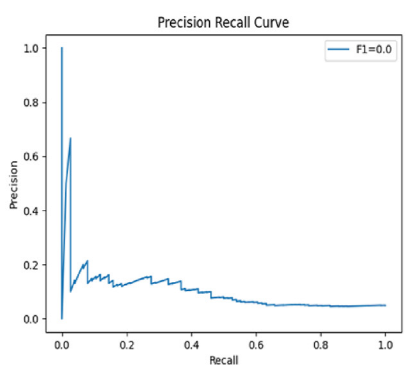
(B) ROC Curve of Logistic Regression



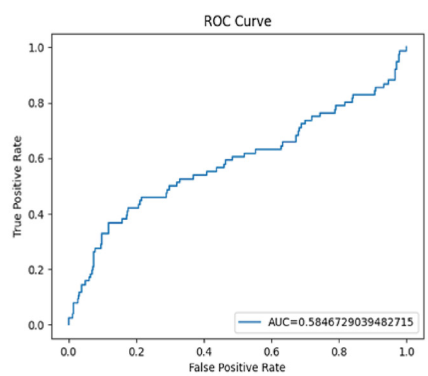
(C) Precision & Recall Curve of Naïve Bayes



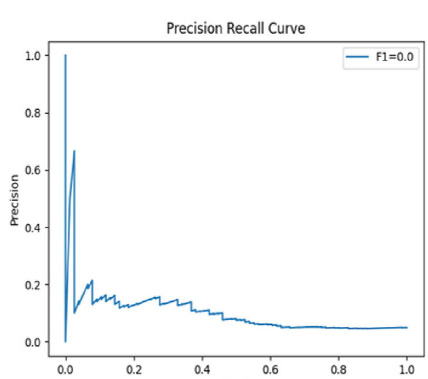
(D) ROC Curve of Naïve Bayes



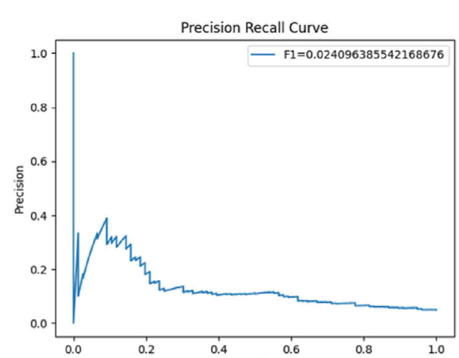
(E) Precision & Recall Curve of SVM



(F) ROC Curve of SVM



(G) Precision & Recall Curve of XGBoost



(H) Precision & Recall Curve of XGBoost

Fig. 3. Precision, recall, and receiver operating characteristic (ROC) curves of different classifiers (A–B: Logistic Regression, C–D: Naive Bayes, E–F: SVM and G–H: XGBoost).

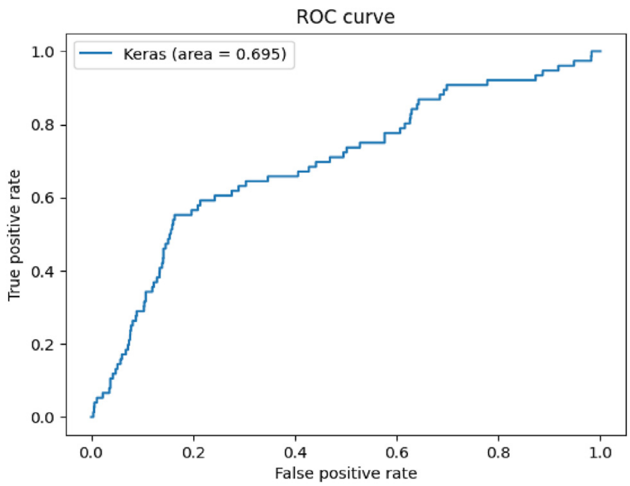


Fig. 4. ROC curve of Neural Network.

XGBoost is an optimized implementation of gradient boosting. Although this model demonstrates competitive performance, it produces slightly lower accuracy than the other models. However, it remains a valuable technique in stroke prediction tasks, with high accuracy and efficient training.

In conclusion, the eight machine learning techniques used for stroke prediction produced promising results, with high levels of accuracy achieved by LR, SVM, KNN, RF, and NN. These models have the potential to contribute significantly to accurate stroke risk assessment and aid in the development of personalized preventive strategies. The choice of technique should consider factors such as interpretability, computational requirements, and the specific goals of the stroke prediction task.

The metrics used to carry out performance analysis of the algorithm are the accuracy score, precision (P), recall (R), F-measure, and receiver operating characteristic (ROC) curve. Graphical comparison of the various algorithms using these metrics is presented in Figs. 2–4.

Model Validation: It is essential to conduct thorough model validation with separate datasets to guarantee robust performance and generalizability across various patient groups. In this research, the training set was split into k subsets, or folds, for k-fold cross-validation. The model was trained $k = 5$ times, using $k-1$ folds for training and 1-fold for validation each time. This process is repeated for every fold, and the performance indicators are averaged over all folds.

A split ratio of 80%/20% for the training and test sets was used in this research.

The L2 regularization method was applied to avoid overfitting. Overly complex models are penalized by regularization, and early stopping ends the training process when the model performance begins to deteriorate on the validation set.

5. Comparative analysis of techniques

Naive Bayes: The NB classifier achieved an accuracy of 88.12% in stroke prediction. This is lower than other techniques in this study, although NB remains a popular choice for its simplicity and efficiency in handling large datasets.

Logistic Regression: LR attained an accuracy of 95.04% in stroke prediction. This widely used statistical model estimates the probability of an event occurring. LR performs well when the

Table 3
Comparative analysis of different algorithms.

Technique	Accuracy (%)	Advantages	Limitations
Naive Bayes	88.12	-Simple and efficient -Works well with large datasets	-Assumes independence among features -May not capture complex relationships
Logistic Regression	95.04	-Interpretable -Handles linear relationships effectively	-Assumes linear relationships -May not capture nonlinear interactions
Support Vector Machines (SVM)	95.04	-Handles linear and nonlinear relationships effectively -Can use kernel functions for flexible modeling	-Computational complexity increases with larger datasets and more complex kernels
K-Nearest Neighbors (KNN)	95.04	-Non-parametric and versatile -Effective with local patterns	-Can be computationally expensive with large datasets
Decision Tree	91.15	-Interpretable -Captures feature interactions	-Prone to overfitting -Limited performance with complex relationships
Random Forest	95.17	-Accurate and robust -Handles complex relationships effectively	-Lack of interpretability -Computationally intensive with large number of trees
XGBoost	94.65	-High accuracy -Efficient training -Handles complex relationships effectively	-May require tuning of hyperparameters -Lack of interpretability
Neural Network	95.45	-Captures complex patterns and relationships effectively -High accuracy -Potential for hierarchical feature representation	-Requires more data and computational resources -Lack of interpretability (black box nature)

Table 4
Analysis of different machine learning algorithms.

Algorithm	Precision	Recall	F-measure	Accuracy (%)
Naive Bayes	92.57	88.12	90.1	88.12
Logistic Regression	90.33	95.04	92.63	95.04
KNN	90.33	95.04	92.63	95.04
Decision Tree	91.93	91.51	91.72	91.51
Random Forest	95.4	95.17	92.94	95.17
XG Boost	92.14	94.65	92.96	94.65
SVM	90.33	95.04	92.63	95.04
Neural Network	97.55	94.91	92.92	95.45

relationship between predictors and the outcome is relatively linear. Its high accuracy suggests that the relationship between the selected features and stroke risk can be effectively captured by this method.

Support Vector Machines: SVM achieved an accuracy of 95.04% in stroke prediction, matching the accuracy of LR. This model can handle both linear and nonlinear relationships through the use of kernel functions. In this study, SVM demonstrated its ability to effectively classify individuals at risk of stroke.

K-Nearest Neighbors: KNN also achieved an accuracy of 95.04% in stroke prediction, the same as LR and SVM. The comparable accuracy of KNN further supports its suitability for stroke risk assessment.

Decision Tree: The DT algorithm achieved an accuracy of 91.15% in stroke prediction. While DTs offer interpretability, their accuracy can sometimes be lower than that of other techniques, especially when dealing with complex relationships and interactions among features.

Random Forest: The RF model achieved an accuracy of 95.17% in stroke prediction. In this study, RF exhibited competitive performance, indicating its effectiveness in capturing complex patterns associated with stroke risk.

XGBoost: XGBoost achieved an accuracy of 94.65% in stroke prediction.

Neural Network: The NN model attained the highest accuracy of 95.45% in stroke prediction. The high accuracy achieved by the NN in this study underscores its efficacy as a powerful tool for stroke risk assessment.

In summary, the comparative analysis highlights the performance of various techniques in stroke prediction. LR, SVM, KNN, RF, and the NN demonstrated comparable high accuracies, outperforming NB, DT, and XGBoost. The results (summarized in Tables 3 and 4) suggest that these techniques, especially the NN, have the potential to contribute significantly to accurate stroke risk assessment and aid in the development of personalized preventive strategies.

6. Conclusions

This section presents the conclusion of this work by highlighting the challenges, limitations and future scope of the presented work.

6.1. Challenges and limitations of the research conducted in this study

The major challenge of applying machine learning algorithms to predict heart stroke risk was the missing data in the clinical information of the dataset, which created a barrier in the feature selection process.

One limitation of this research was the size of the dataset used. The results of this research could be further affirmed by using larger real datasets for heart stroke prediction. Hybrid models using superior machine learning classifiers should also be implemented and tested for stroke prediction.

Turkyilmazoglu et al.[24,25] described other nonlinear regression techniques that can provide different results for heart stroke prediction. The algorithms considered in the present study could be improved by using ensemble models, enhancing the data quality, and applying the SMOTE algorithm for imbalanced datasets.

6.2. Conclusion and future scope

In conclusion, our research aimed to compare the predictive performance of various machine learning algorithms on a heart stroke dataset. Through rigorous experimentation and evaluation, we found that the NN model emerged as the most effective technique. The results revealed that NB exhibited the lowest accuracy among the tested methods. These findings underscore the power and versatility of NNs in accurately predicting stroke occurrences, highlighting their potential for aiding in early detection and prevention strategies. As machine learning continues to advance, further investigations will explore the optimization of NNs and their application in the field of medical research and healthcare.

In future work, the performance of the algorithms considered in this study could be improved through the integration of sophisticated preprocessing techniques and feature engineering methodologies. Moreover, adding more complete and varied datasets that cover a larger spectrum of clinical and demographic characteristics may help create a more reliable and broadly applicable stroke prediction model. Additionally, by using methods like feature importance analysis and model visualization, it may be possible to investigate the interpretability of neural networks, giving researchers and physicians a better understanding of the fundamental variables that influence the risk of stroke. The usage of these models in actual clinical settings could also be studied, with an emphasis on creating approachable tools and user interfaces for the prospective adoption of machine learning in stroke prediction.

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Author contributions

All authors discussed the contents of the manuscript and contributed to its preparation. AG and NM contributed the idea and performed calculations in interpretation. NJ, SM, and FA, KAG, SNM helped in the analysis of the results and in the writing of the manuscript. NM helped AG, NJ and SM in applying the concept to the proposed model.

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Declaration of competing interest

The authors declare that they have no conflict of interest, and the paper presents their own work which does not infringe any third-party rights. Authorship of any part of the article is an original contribution that has not been published before and is not under consideration for publication elsewhere.

Data availability statement

Data are available on the Kaggle website: https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset.

Ethical approval

Not applicable.

Informed consent

Not applicable.

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