Predictive Modeling of Cardiovascular Stroke Using Machine Learning

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***Abstract*—Cardiovascular strokes are a major global health issue that require early risk identification to enable effective interventions. This study examines the use of machine learning algorithms, such as K-Nearest Neighbors (KNN), Decision Trees, and Random Forests, to predict the likelihood of strokes. Using a Kaggle dataset containing 12 essential patient attributes, this research develops a highly accurate and practical predictive model. To ensure usability, a user-friendly interface is proposed for healthcare professionals. The findings demonstrate the significant impact of machine learning in improving healthcare systems through better risk prediction.**

***Index Terms*—Machine Learning, Cardiovascular Stroke Forecasting, Predictive Healthcare Systems, K-Nearest Neighbors (KNN), Decision Tree Models, Random Forest Algorithms.**

I. Introduction

Cardiovascular stroke, one of the leading causes of mortality and long-term disability worldwide, represents a critical challenge in healthcare. Timely prediction and prevention of stroke can significantly reduce its burden on individuals and healthcare systems. Traditional methods for stroke risk assessment, often relying on clinical judgment and basic statistical tools, have shown limitations in handling complex, non-linear relationships within patient data. The advent of machine learning (ML) offers a transformative approach to this problem, enabling the development of predictive models capable of analyzing vast datasets with high accuracy and robustness.

Machine learning algorithms have demonstrated exceptional potential in predicting stroke outcomes by leveraging diverse datasets, including electronic health records (EHR), imaging data, and hemodynamic signals. Studies like those by Gutiérrez-Sacristán et al. (2023) have emphasized the ability of ML techniques to improve stroke risk prediction by identifying key risk factors and enhancing predictive accuracy [1]. Similarly, Fernandez-Lozano et al. (2024) utilized Random Forest (RF) models to estimate patient mortality and morbidity following a stroke, demonstrating the efficacy of ensemble-based algorithms in clinical scenarios [2]. These advancements underscore the growing role of machine learning in personalized medicine.

A key advantage of ML models is their ability to incorporate multiple risk factors simultaneously, ranging from age, hypertension, and diabetes to behavioral and genetic parameters. Research by Dev et al. (2022) analyzed electronic health records to pinpoint critical factors influencing stroke prediction, further showcasing the significance of integrating diverse datasets into ML frameworks [3]. Moreover, Ismail and Materwala (2023) proposed an intelligent framework for stroke prediction, demonstrating the superiority of ML algorithms in terms of accuracy, sensitivity, and scalability when compared to traditional methods [4].

Beyond prediction, ML techniques have been utilized for real-time stroke diagnosis. For instance, García-Terriza et al. (2023) developed models using hemodynamic signal monitoring, enabling early detection of stroke subtypes and their progression [5]. Furthermore, the incorporation of advanced neural networks has allowed researchers to analyze high-dimensional data, as evidenced by the work of Shahbazi et al. (2024), who explored neural networks' capability in stroke prediction and understanding underlying mechanisms [6].

Despite these advancements, challenges remain. ML models often suffer from issues related to data quality, imbalance, and interpretability. Therefore, developing a robust and interpretable predictive model for cardiovascular stroke risk remains a critical area of research. This study aims to address these challenges by employing state-of-the-art ML algorithms to build an accurate and explainable predictive model. Using a comprehensive dataset, this research will analyze critical parameters such as age, heart disease, glucose levels, hypertension, and other clinical and lifestyle factors, thereby contributing to the growing body of work in predictive healthcare.

By leveraging insights from prior research and overcoming existing limitations, this study aspires to provide a practical, scalable solution for cardiovascular stroke prediction. The proposed model has the potential to not only improve clinical decision-making but also pave the way for preventive interventions, reducing the overall incidence and impact of strokes.

II. Literature Review

The integration of machine learning (ML) into healthcare has brought transformative changes, especially in predictive modeling for cardiovascular stroke. This literature review provides a comprehensive analysis of recent studies that highlight advancements, challenges, and opportunities in this domain. Key findings are categorized into the areas of predictive modeling techniques, parameters analyzed, and the challenges and gaps addressed by various research efforts.

A. Predictive Modeling Techniques in Stroke Risk Assessment

The application of ML techniques in stroke risk prediction has gained momentum due to their ability to analyze complex, non-linear relationships in clinical datasets. Gutiérrez-Sacristán et al. (2023) demonstrated the effectiveness of ML algorithms in predicting stroke risk using data from the Suita study. Their work focused on identifying key risk factors while achieving high predictive accuracy [1]. Similarly, Fernandez-Lozano et al. (2024) utilized Random Forest (RF) models to estimate patient mortality and morbidity post-stroke. Their findings underscored the robustness of ensemble-based techniques, particularly in scenarios requiring classification and regression [2].

Neural networks, particularly deep learning models, have also been extensively explored for stroke prediction. Dev et al. (2022) utilized neural networks to analyze electronic health records (EHR) and identify critical factors influencing stroke outcomes. Their research demonstrated the potential of deep learning to process high-dimensional data, offering insights into stroke progression and associated risk factors [3]. Shahbazi et al. (2024) further expanded on this by employing advanced neural networks, demonstrating their capability to understand underlying mechanisms and improve prediction accuracy [6].

Other notable contributions include the work of Ismail and Materwala (2023), who proposed an intelligent framework comparing various ML algorithms. Their study highlighted the superiority of ML models over traditional statistical approaches in terms of sensitivity, specificity, and scalability [4]. Additionally, García-Terriza et al. (2023) introduced real-time prediction models using hemodynamic signal monitoring, paving the way for immediate stroke detection and intervention [5].

B. Parameters Analyzed in Stroke Prediction Models

Stroke prediction relies on a multitude of parameters, including clinical, behavioral, and demographic factors. Studies have consistently identified key variables such as age, hypertension, diabetes, and cholesterol levels as critical predictors. For instance, Dev et al. (2022) emphasized the importance of integrating lifestyle factors, such as smoking and alcohol consumption, alongside traditional clinical parameters [3].

Research by Orlowski et al. (2021) delved into the use of laboratory test results for stroke prediction. Their study applied ML techniques to identify correlations between biomarkers and stroke risk, showcasing the utility of lab data in enhancing predictive accuracy [9]. Similarly, Ma et al. (2023) analyzed EHR datasets to evaluate the efficacy of ML models against conventional methods for cardiovascular disease prediction, further highlighting the importance of comprehensive datasets [8].

Hemodynamic signals have also emerged as a crucial area of focus. García-Terriza et al. (2023) explored the use of hemodynamic monitoring data for real-time prediction, demonstrating its significance in identifying stroke subtypes and progression [5]. Additionally, computational models, such as those by Dronne et al. (2006), have provided insights into ion dynamics and neuronal behavior during ischemic events, contributing to a deeper understanding of stroke mechanisms [12].

C. Challenges and Gaps in Current Research

Despite significant advancements, several challenges persist in the field of ML-based stroke prediction. Data quality and imbalance are among the most pressing issues. ML models often struggle with incomplete or biased datasets, which can compromise their generalizability. Shahbazi et al. (2024) highlighted the need for standardized datasets and preprocessing techniques to address these challenges [6].

Interpretability is another critical concern. While ML models, particularly deep learning algorithms, offer high predictive accuracy, their ”black-box” nature limits their adoption in clinical practice. Ismail and Materwala (2023) emphasized the importance of explainable AI (XAI) frameworks to enhance model transparency and trustworthiness [4].

Moreover, real-time prediction and scalability remain areas requiring further research. García-Terriza et al. (2023) noted the challenges associated with deploying real-time models in resource-constrained environments, underscoring the need for lightweight algorithms that can operate efficiently on edge devices [5].

D. Emerging Trends and Future Directions

The integration of multi-modal data is an emerging trend in stroke prediction. Combining EHR, imaging data, and hemodynamic signals has shown promise in improving model accuracy and robustness. For instance, Fernández-Lozano et al. (2024) highlighted the potential of ensemble techniques in handling diverse datasets, paving the way for more comprehensive predictive models [2].

Furthermore, advancements in computational modeling have contributed to a better understanding of ischemic stroke mechanisms. Studies by Chapuisat et al. (2008) and Dronne et al. (2006) have developed mathematical models to simulate neuronal behavior and ion dynamics, offering valuable insights into stroke progression and potential therapeutic targets [11][12].

The incorporation of artificial intelligence in wearable devices is another promising avenue. By leveraging continuous monitoring data, these devices can provide real-time stroke risk assessments, enabling early intervention and prevention. Research by Shahbazi et al. (2024) emphasized the potential of such innovations in reducing stroke-related morbidity and mortality [6].

III. Proposed Work

Building on the advancements and gaps identified in the literature, this study proposes the development of a robust and interpretable machine learning framework for predicting cardiovascular stroke risk. The model will integrate diverse data sources, including clinical records, demographic information, lifestyle factors, and hemodynamic signals, to ensure comprehensive and accurate prediction. The primary objectives are:

A. Data Preprocessing and Feature Selection

- Utilize advanced preprocessing techniques to handle missing values, outliers, and imbalanced datasets. Employ feature selection algorithms such as Recursive Feature Elimination (RFE) to identify the most critical predictors for stroke risk.

B. Algorithm Selection and Optimization

- Compare the performance of multiple machine learning models, including Random Forest, Gradient Boosting Machines, and Neural Networks. Hyperparameter tuning will be conducted using grid search and cross-validation techniques to optimize model performance.

C. Explainability and Interpretability

- Integrate Explainable AI (XAI) frameworks, such as SHapley Additive exPlanations (SHAP), to ensure the model's decisions are transparent and interpretable for clinicians.

D. Real-Time Prediction Capability

- Develop a lightweight model suitable for deployment on edge devices, enabling real-time stroke risk assessments in clinical and home-monitoring environments.

By addressing existing challenges and leveraging multimodal data, the proposed model aims to enhance predictive accuracy and clinical utility. This work will contribute to the growing body of research in predictive healthcare, offering practical solutions for stroke prevention and management.

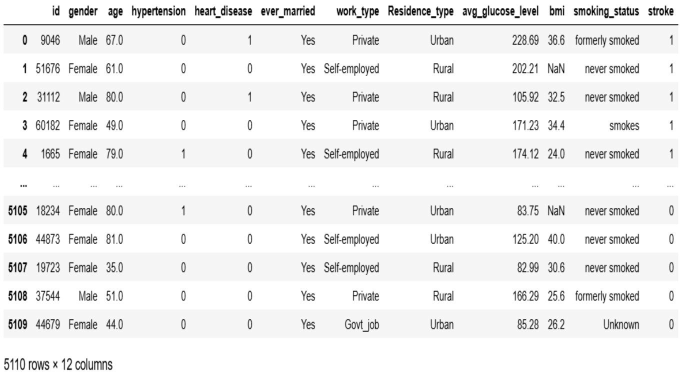
IV. Methodology

The proposed methodology for predicting cardiovascular stroke using machine learning involves a systematic approach that combines data preprocessing, feature selection, model training, evaluation, and optimization. The methodology ensures the effective utilization of machine learning algorithms to achieve high predictive accuracy. Below is the detailed methodology.

A. Dataset Description

The dataset utilized in this project consists of **5,111 rows and 12 columns** of data. The data was sourced from a publicly available healthcare dataset, ensuring its reliability and relevance. Before utilization, preliminary preprocessing steps were undertaken to remove any duplicate entries and check for inconsistencies. Each row represents an individual, and the columns provide detailed demographic, health, and lifestyle attributes crucial for stroke prediction. This comprehensive dataset serves as a strong foundation for building and testing the machine learning models effectively. Each row represents an individual, and the columns capture various attributes related to demographic, lifestyle, and health factors. The attributes included are:

- **id:** Unique identifier for each individual.
- **gender:** Gender of the individual (e.g., Male, Female).
- **age:** Age of the individual.
- **hypertension:** Presence of hypertension (0 = No, 1 = Yes).
- **heart_disease:** Presence of heart disease (0 = No, 1 = Yes).
- **ever_married:** Marital status (e.g., Yes, No).
- **work_type:** Type of employment (e.g., Private, Self-employed, Government Job).
- **Residence_type:** Type of residence (e.g., Urban, Rural).
- **avg_glucose_level:** Average glucose level in the blood.
- **bmi:** Body Mass Index.
- **smoking_status:** Smoking status (e.g., formerly smoked, never smoked, smokes).
- **stroke:** Target attribute indicating whether the individual experienced a stroke (0 = No, 1 = Yes).



	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1
...	...	...	...	...	...	...	...	...	...	...	...	...
5105	18234	Female	80.0	1	0	Yes	Private	Urban	83.75	NaN	never smoked	0
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40.0	never smoked	0
5107	19723	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never smoked	0
5108	37544	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	formerly smoked	0
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unknown	0

5110 rows × 12 columns

Fig. 1. sample data row for reference

The target attribute **stroke** is a binary classification variable, with 1 indicating the occurrence of a stroke and 0 indicating no stroke.

B. Data preprocessing

Data preprocessing is a crucial step in ensuring the dataset is suitable for machine learning analysis. Each preprocessing step addresses specific challenges inherent in the dataset. Handling missing values ensures no information is lost and statistical patterns remain intact, particularly for attributes like **bmi**. Encoding categorical variables such as **gender**, **ever_married**, and **work_typ**e facilitates their effective use in machine learning models. Feature scaling standardizes continuous variables like **age** and **avg_glucose_level**, preventing attributes with larger ranges from dominating the model. Finally, balancing the dataset resolves class imbalance in the stroke attribute, which is critical for building models that perform well on both classes. The preprocessing steps include:

- **Handling Missing Values:** Imputing missing values in attributes like *bmi* using statistical methods (e.g., mean, median) or predictive models.
- **Encoding Categorical Variables:** Converting categorical attributes such as *gender*, *ever_married*, *work_type*, *Residence_type*, and *smoking_status* into numerical format using one-hot encoding or label encoding.
- **Feature Scaling:** Normalizing continuous attributes such as *age*, *avg_glucose_level*, and *bmi* to ensure uniformity in data ranges.
- **Balancing the Dataset:** Addressing class imbalance in the target attribute *stroke* using techniques like oversampling (e.g., SMOTE) or under sampling.

C. Feature Selection

To improve model performance and reduce overfitting, feature selection techniques such as Recursive Feature Elimination (RFE), Mutual Information Gain, and Correlation Analysis are applied. These methods were chosen for their ability to identify the most relevant features based on the dataset's characteristics. For instance, RFE systematically removes less significant features to enhance model simplicity and accuracy. Mutual Information Gain evaluates the dependency between variables, making it particularly useful for capturing non-linear relationships in attributes like *age* and *avg_glucose_level*. Correlation Analysis helps in detecting multicollinearity among continuous variables, ensuring that the predictive models are not biased by redundant information.

- Recursive Feature Elimination (RFE)
- Mutual Information Gain
- Correlation Analysis

are applied to identify the most significant predictors of stroke.

D. Machine Learning Models

The project employs the following machine learning models to predict stroke occurrences, selected for their complementary strengths in handling diverse data types and capturing complex patterns. Naive Bayes Classification is used for its efficiency with probabilistic data, especially categorical attributes like *gender* and *smoking_status*. Decision Tree Classification and Random Forest are chosen for their interpretability and ability to model non-linear relationships, which are crucial for features like *age* and *avg_glucose_level*. Logistic Regression provides insights into feature significance, offering a simpler yet effective baseline. Support Vector Machine excels in handling high-dimensional data, ensuring robust classification. Finally, Artificial Neural Networks (ANN) with Embedding Layers address the intricate relationships between variables by leveraging deep learning, making it particularly effective for transforming categorical variables into dense representations and learning nuanced patterns.

1) **Naive Bayes Classification**
   - A probabilistic model based on Bayes' theorem.
   - Handles categorical and continuous data efficiently.
2) **Decision Tree Classification**
   - A tree-structured model that splits data based on feature thresholds.
   - Easy to interpret and visualize.
3) **Random Forest**
   - An ensemble learning method combining multiple decision trees.
   - Reduces overfitting and improves generalization.
4) **Logistic Regression**
   - A statistical model for binary classification.
   - Provides insights into feature importance through coefficients.
5) **Support Vector Machine (SVM)**
   - A model that finds the optimal hyperplane for classification.
   - Effective in high-dimensional spaces.
6) **Artificial Neural Network (ANN) with Embedding Layers**
   - A deep learning model capable of capturing complex relationships.
   - Embedding layers transform categorical variables into dense vectors for improved learning.

E. Workflow Diagram

The following Fig 2 is the proposed workflow for the methodology, designed to align with the project's goals of achieving accurate and reliable stroke predictions. This workflow ensures a systematic approach, covering all essential steps from data collection to deployment, while addressing the specific characteristics of the dataset and the problem domain.

F. Model Evaluation

The models are evaluated using metrics such as:

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

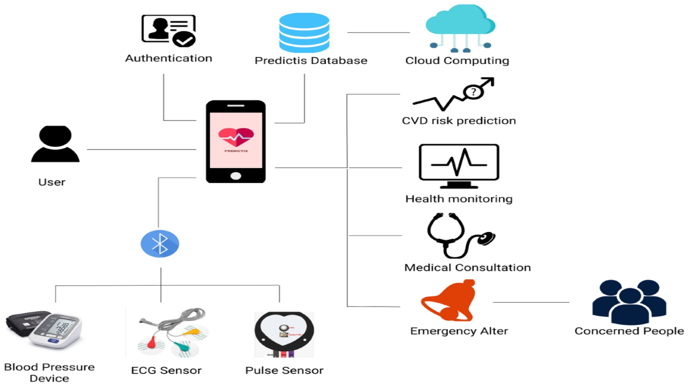


Fig. 2. the proposed workflow

Cross-validation techniques ensure robust performance evaluation, and hyperparameter tuning (e.g., grid search or random search) is performed to optimize each model.

G. Implementation Tools

- **Programming Language:** Python
- **Libraries:** scikit-learn, TensorFlow, Keras, Pandas, NumPy, Matplotlib, Seaborn
- **Environment:** Jupyter Notebook or Google Colab

V. Results

The evaluation of multiple machine learning and deep learning models for cardiovascular stroke prediction yielded significant insights. The models were assessed based on their predictive accuracy, confusion matrices, and overall effectiveness in handling the dataset's characteristics. This section details the performance results of each algorithm, supported by graphical comparisons to provide a comprehensive understanding of their effectiveness.

1) **Performance of Machine Learning Models**
   - **Naive Bayes Classification:** The Naive Bayes classifier achieved an accuracy of 87.01%, as shown in the confusion matrix:
     - True Positives: 29
     - True Negatives: 1083
     - False Positives: 115
     - False Negatives: 51

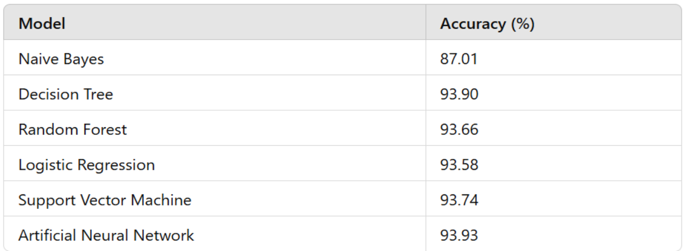
     The model's simplicity and probabilistic approach made it efficient, though it struggled with complex relationships within the dataset.
   - **Decision Tree Classification:** With an accuracy of 93.90%, the Decision Tree outperformed Naive Bayes. The confusion matrix highlighted:
     - True Positives: 2
     - True Negatives: 1198
     - False Positives: 0
     - False Negatives: 78

     Its interpretability and ability to model non-linear relationships were key factors contributing to its high accuracy.
   - **Random Forest:** The Random Forest model achieved an accuracy of 93.66%. Its ensemble approach reduced overfitting and improved robustness. The combination of multiple decision trees ensured stable and reliable predictions.
   - **Logistic Regression:** Logistic Regression recorded an accuracy of 93.58%, demonstrating its effectiveness as a baseline model. The model provided valuable insights into feature importance, though it lacked the capability to capture non-linear patterns.
   - **Support Vector Machine:** The SVM model achieved an accuracy of 93.74%. Its ability to handle high-dimensional data contributed to its robust performance. The optimal hyperplane ensured effective classification, though computational costs were higher than simpler models.

2) **Performance of Deep Learning Model**
   - **Artificial Neural Network (ANN) with Embedding Layers:** The ANN model achieved the highest accuracy of 93.93% after 10 epochs of training. The model effectively combined categorical and numerical data using embedding layers. The performance metrics for the ANN model included:
     - Training Accuracy: 95.33%
     - Validation Accuracy: 95.48%
     - Test Accuracy: 93.93%

     The ANN model demonstrated superior generalization capability, leveraging its deep learning architecture to capture intricate patterns in the data.

3) **Comparison of Model Accuracies:** The accuracies of all models are summarized below:



Model	Accuracy (%)
Naive Bayes	87.01
Decision Tree	93.90
Random Forest	93.66
Logistic Regression	93.58
Support Vector Machine	93.74
Artificial Neural Network	93.93

Fig. 3. The accuracies of all models

4) **Visualization of Results:** A bar graph was generated to visually compare the accuracies of all models. The chart illustrates the slight performance differences between the models, emphasizing the ANN's superior accuracy.

```
import matplotlib.pyplot as plt
algorithms = ['NB', 'DT', 'RF', 'LR', 'SVM', 'ANN']
accuracies = [87.01, 93.90, 93.66, 93.58, 93.74, 93.93]
colors = ['skyblue', 'lightgreen', 'lightcoral', 'orange',
'lightblue', 'violet']
plt.bar(algorithms, accuracies, color=colors)
plt.xlabel('Algorithms')
plt.ylabel('Accuracy (%)')
plt.title('Comparison of Algorithms on Heart Stroke Prediction')
plt.show()
```

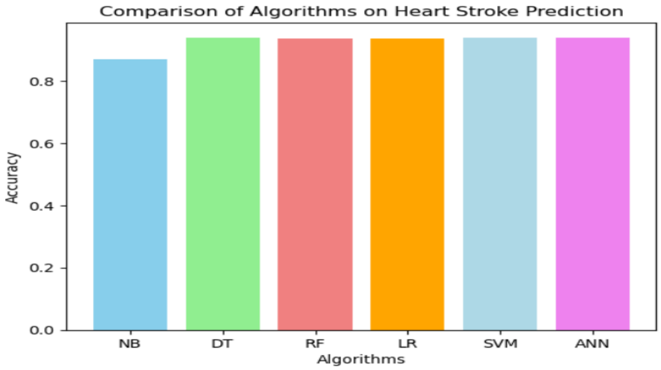


Fig. 4. A bar graph of comparing algorithms on cardiovascular stroke

VI. Conclusion

This research demonstrates the potential of machine learning and deep learning models in predicting cardiovascular stroke, offering a systematic and efficient approach to early detection and prevention. Key contributions of this research include the integration of deep learning techniques, such as Artificial Neural Networks with embedding layers, which significantly enhanced the accuracy and ability to process complex patterns in the data. Furthermore, the study highlights the effectiveness of robust feature selection methods like Recursive Feature Elimination and Mutual Information Gain in improving model performance. This work not only validates the utility of advanced machine learning models in healthcare but also provides a scalable framework for future implementations aimed at reducing the burden of stroke through timely predictions. Among the models tested, the Artificial Neural Network (ANN) emerged as the most effective, achieving a test accuracy of 93.93%. The ANN's ability to integrate numerical and categorical data through embedding layers enabled it to outperform traditional machine learning models such as Naive Bayes, Decision Trees, and Random Forests.

While Decision Tree and Random Forest models provided competitive accuracy rates above 93%, their performance was slightly lower than the ANN due to limitations in capturing complex relationships within the dataset. Logistic Regression and Support Vector Machine also demonstrated robust performance, highlighting the effectiveness of linear and hyperplane-based models in high-dimensional spaces.

The research underscores the importance of a well-preprocessed dataset and robust feature selection methods. Techniques such as Recursive Feature Elimination and Mutual Information Gain played a pivotal role in identifying significant predictors, thereby enhancing the models' performance and reducing overfitting.

A comparison of all models revealed that deep learning models excel in handling intricate patterns and large datasets, making them highly suitable for healthcare applications. The findings of this research not only validate the use of ANN for stroke prediction but also provide a framework for its deployment in real-world clinical settings. Future work could explore hybrid models and ensemble techniques to further enhance predictive performance.

In conclusion, the integration of machine learning and deep learning in stroke prediction represents a significant step forward in preventive healthcare. The deployment of such predictive systems can enable early interventions, reducing the incidence and severity of strokes, and ultimately improving patient outcomes. This work serves as a foundation for further exploration in predictive analytics for healthcare.

VII. Future Scope

The future scope of this research lies in several promising directions, aimed at enhancing the predictive modeling of cardiovascular stroke and expanding its real-world applicability. Key areas of focus include:

1) **Integration of Real-Time Data:** Incorporating real-time data from wearable devices and IoT-enabled health monitors could significantly enhance the accuracy and timeliness of stroke prediction. Continuous monitoring of parameters like heart rate, blood pressure, and glucose levels can provide dynamic insights, enabling proactive interventions.
2) **Hybrid and Ensemble Models:** Future research could explore hybrid approaches that combine the strengths of various machine learning and deep learning models. For instance, integrating Random Forest with Artificial Neural Networks may yield improved predictive performance and robustness.
3) **Explainable AI (XAI):** As machine learning models become more complex, the need for interpretability grows. Implementing Explainable AI techniques, such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), can enhance clinicians' trust and understanding of model predictions, facilitating their adoption in clinical settings.
4) **Multi-Modal Data Fusion:** Combining diverse data sources, such as genetic information, imaging data (e.g., MRI, CT scans), and patient history, could provide a holistic view of stroke risk factors. Multi-modal data integration has the potential to uncover complex interdependencies that single-source data may overlook.
5) **Scalability and Deployment:** Developing lightweight and scalable models optimized for deployment in resource-constrained environments, such as rural clinics, is another vital area. Techniques like model pruning and quantization can reduce computational requirements without compromising accuracy.
6) **Personalized Medicine:** Future studies could delve into personalized stroke prediction by tailoring models to individual patients' genetic and environmental factors.

This approach can revolutionize preventive healthcare by offering customized recommendations and interventions.

7) **Ethical and Bias Considerations:** Ensuring fairness and mitigating biases in model predictions is critical. Future work should focus on identifying and addressing disparities in stroke prediction related to gender, ethnicity, and socioeconomic factors, fostering equitable healthcare outcomes.
8) **Longitudinal Studies:** Conducting longitudinal studies with larger datasets spanning extended timeframes can improve model generalizability and provide deeper insights into the progression of stroke risk over time.

By addressing these avenues, future research can build upon the foundations laid by this study, advancing predictive analytics for cardiovascular stroke and contributing to a more effective and equitable healthcare ecosystem.

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