The Comprehensive Investigation of Machine Learning-Based Patient Brain Stroke Prediction

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Abstract: This paper aims to comprehensively review machine learning methodologies for stroke prediction, evaluating both traditional and deep learning approaches, and discussing challenges and potential solutions in this domain. The paper conducts a thorough examination of machine learning methodologies for stroke prediction. Traditional techniques are scrutinized for their efficacy in handling stroke prediction tasks across various datasets. Deep learning approaches such as U-Net and Generative Adversarial Networks are also investigated to assess their suitability and performance. Moreover, the review delves into the intricacies of these methods, considering factors such as interpretability, privacy concerns, and data quality issues. Additionally, it explores novel techniques such as the Shapley Addition Method of Interpretation and Federated Learning (FL) as potential solutions to enhance interpretability and protect patient privacy. The review also examines the potential of transfer learning to optimize model generalization across different domains, aiming to provide insights into the most effective methodologies for stroke prediction. Findings suggest the promise of machine learning in stroke prediction. Future research directions include integrating emerging techniques such as large language models and multimodal data fusion for improved accuracy guiding researchers and practitioners in selecting appropriate Machine Learning methods and addressing challenges in stroke prediction for enhanced patient care.

1 INTRODUCTION

A stroke, a neurological condition, arises from sudden, localized damage to the central nervous system due to vascular problems, encompassing cerebral infarction, Intracerebral hemorrhage (ICH) (Qiu, 2020), and Subarachnoid hemorrhage (SAH). It significantly impacts global disability and mortality rates. Each year, stroke claims the lives of roughly 4.6 million individuals, amounting to about 9 percent of global deaths. Beyond its lethal impact, stroke also leads to substantial nonfatal health issues and disabilities. While research from developed nations shows that targeted interventions at individual, community, and national levels can significantly reduce the occurrence of stroke and related vascular conditions, this knowledge has not been uniformly implemented in developing regions. The frequency of stroke differs markedly between populations, with risk escalating with age or unhealthy lifestyle choices (Azam, 2020). Within the contemporary clinical realm, the diagnostic procedure for identifying stroke is often marked by its laborious and ineffective nature, frequently failing to efficiently manage time and human resources while occasionally leading to increased rates of misdiagnosis. Consequently, there arises an urgent imperative to explore alternative methodologies for stroke prediction, with a specific emphasis on harnessing the capabilities of Artificial Intelligence (AI) model due to their excellent performance in many tasks (Sun, 2020; Wu, 2024).

This transition towards AI-based stroke prediction represents a significant departure from traditional diagnostic approaches and holds considerable promise in augmenting the efficiency and precision of diagnostic protocols, ultimately culminating in enhanced patient outcomes and optimized allocation of healthcare resources. In a recent study, researchers utilized retrospective data to evaluate two distinct algorithmic approaches: An algorithm validated through statistical methods and another trained by clinicians. Their findings revealed that the

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implementation of Random Forest demonstrated superior prediction accuracy compared to the clinician-trained algorithms. Specifically, the Random Forest model exhibited heightened sensitivity and only marginally reduced specificity, indicating its effectiveness in predicting outcomes (Cox, 2016). Subsequently, researchers evaluated three distinct supervised Machine Learning (ML) models: Random Forests (RF), Gradient Boosting, and U-Net. Of these ML models, Gradient Boosting emerged as notably pertinent for forecasting tissue outcomes following acute ischemic stroke (AIS), closely trailed by Random Forests and U-Net in terms of effectiveness (Benzakoun, 2021). In another study, three prominent classification methods - Neural Network (NN), Decision Tree (DT), and Random Forest (RF) - were compared to predict stroke occurrence based on patient attributes. All three machine learning models were trained on a balanced dataset comprising 28,524 patient records. The analysis revealed that the features were not strongly correlated, and it was observed that a combination of merely four features could significantly contribute to accurate stroke prediction (Dev, 2022). CT scans serve as a commonly utilized dataset in the context of stroke research and diagnosis (Sirsat, 2020), Numerous research papers have adopted a hybrid machine learning strategy to forecast stroke occurrence using incomplete and unbalanced medical datasets, recognizing the diverse implications of employing different datasets in ML analysis (Liu, 2019).

This paper focuses on getting the current better datasets and machine learning methods by examining and discussing the various machine learning studies conducted on different datasets. The paper proceeds as outlined below: First, this paper will examine the various machine learning methods employed in literature to analyze and test diverse datasets in section 2. Section 3 will delve into the insights derived from numerous comparative analyses, focusing on identifying and addressing dataset challenges to enhance the efficacy of machine learning analyses. Finally, Section 4 will provide a summary of the paper and draw conclusions based on the discussions presented in earlier sections.

2 METHOD

The framework of AI-based algorithms in stroke prediction typically integrates both traditional machine learning and deep learning approaches. It initiates with comprehensive data collection, gathering pertinent medical information including demographic details, medical histories, and diagnostic test results. Subsequently, the collected data undergoes meticulous preprocessing to ensure its quality and consistency, facilitating the subsequent analysis. Leveraging a hybrid approach, the model-building phase ensues, where both traditional machine learning algorithms and deep learning architectures are utilized for constructing predictive models. This entails selecting and extracting relevant features from the preprocessed data, a crucial step in enhancing model performance. Following model construction, rigorous training ensues to optimize the models' predictive capabilities, leveraging both machine learning and deep learning techniques to capture complex patterns within the data. Subsequently, the models undergo thorough testing using established evaluation metrics to assess their effectiveness in stroke prediction tasks. Upon successful validation, the models are poised for deployment, the most important is Continuous refinement and improvement.

2.1 Traditional Machine Learning

2.1.1 Random Forest

Fernandez-Lozano, et al. focus on Random Forest-based Stroke Outcome Prediction (Fernandez-Lozano, 2021), identified through a literature review highlighting the superior performance of Random Forests in biomedical applications. Data were collected from 6022 patients, categorized into Ischemic Stroke (IS) and Intracerebral Hemorrhage (ICH) and IS+ ICH groups. After excluding certain patients, the final data set was prepared. The model underwent training using ten-fold cross-validation along with 100 repeated randomizations to ensure robustness and reliability. Analytical forecasts were generated concerning both mortality and morbidity among patient groups diagnosed with ischemic stroke (IS), intracerebral hemorrhage, or a combination of both (IS+ICH). The aim was to determine the primary predictors of machine learning models, particularly Random Forest, for generating predictive models.

2.1.2 Gradient Boosting

Xie, Yuan, et al. utilized an extreme gradient boosting model to examine 512 patients, aiming to forecast the Modified Rankin Score (MRS) at 90 days based on biomarkers accessible upon admission and within 24 hours. The method employed a greedy algorithm for feature selection and assessed model performance through five-fold cross-validation. The results indicate that decision tree-based gradient boosting models exhibit high Area Under the Curve (AUC) in predicting stroke patient recovery outcomes upon admission. Additionally, stratifying patient groups based on recanalization status may offer insights beneficial for treatment decision-making processes (Xie, 2019).

2.1.3 Decision Trees

Kappelhof, et al. introduce a novel algorithm that employs an evolutionary approach to develop decision trees that are both interpretable and powerful for predicting adverse outcomes following Endovascular therapy for acute ischemic stroke (Kappelhof, 2021). Utilizing 5-fold cross-validation, the training cohort comprised an average of 1090 patients, while the validation cohort encompassed 273 patients, achieving an average accuracy rate of 72%. In this decision tree, decision nodes contain split-ranges rather than split-values, which are mathematically defined Employing the notion of belongingness and segmented linear membership functions. The algorithm's primary aim is to balance constraining the size of the tree to maintain interpretability while optimizing prediction accuracy on unseen data. The test algorithm underwent improvement by integrating the function into the operation of the evolutionary algorithm. Initially, decision trees were generated using the grow method as part of the initialization process. Following this, the selection of individuals to advance to the crossover phase and create the subsequent generation took place. The common one-point crossover metho was utilized during this phase. Furthermore, the mutation phase was implemented to introduce variability, with incorrect trees undergoing pruning. Additionally, imputation and experimental setup were integrated into the process. Finally, on average, the fuzzy algorithm converged to its final solution within the initial hour of execution.

2.1.4 Neural Networks

Süt et al. conducted a comprehensive study utilizing Multilayer Perceptron (MLP) neural networks to predict mortality in stroke patients, incorporating a dataset of 584 individuals and examining various prognostic factors. Six distinct MLP algorithms were employed: Quick Propagation (QP), Levenberg-Marquardt (LM), Backpropagation (BP), Quasi-Newton (QN), Delta Bar Delta (DBD), and Conjugate Gradient Descent (CGD) (Süt, 2012). The QP algorithm, despite its potential instability, showcased remarkable efficiency in weight adjustment computation, yielding the highest performance metrics including specificity, sensitivity, accuracy, and area under the curve (AUC). LM, utilizing a least squares estimation method, showed reasonable performance but fell short of QP in predictive accuracy. BP, a widely used technique, demonstrated inferior performance compared to QP despite its simplicity. QN, an advanced training method, did not surpass QP in predictive accuracy despite approximating the inverse Hessian matrix for error gradient calculation. DBD, an alternative to BP, exhibited promising results but did not outperform QP. CGD, employing iterative error gradient and search direction calculations, displayed the lowest predictive accuracy. Overall, the study underscores the pivotal role of algorithm selection in MLP modelling and highlights the potential efficacy of QP-trained models in clinical mortality prediction.

2.2 Deep Learning

2.2.1 U-Net

Li et al. conducted a study aimed at improving care for patients with ischemic stroke by utilizing a sophisticated multi-scale U-Net deep network model (Li, 2021). This model was employed to segment image features extracted from non-enhanced computed tomography (CT) scans of 30 stroke patients. To address the challenge of data imbalance during model training, the authors incorporated the Dice loss function, a metric commonly used in medical image segmentation tasks. This function helps in optimizing the model's performance by penalizing false positives and false negatives, thereby ensuring more accurate segmentation results.

The study involved two primary methods: manual segmentation and automatic segmentation. In manual segmentation, trained radiologists manually delineated the ischemic stroke lesions on the CT scans. On the other hand, automatic segmentation utilized the multi-scale U-Net deep network model to segment the lesions automatically. The comparison between these two methods revealed that the automatic segmentation closely approximated the manual segmentation, indicating the effectiveness of the proposed model in accurately identifying ischemic stroke lesions.

The "lesion area error" refers to the difference between the segmented lesion areas obtained from automatic segmentation and manual segmentation. This metric provides insight into the accuracy of the automatic segmentation method compared to the gold standard manual segmentation. A lower lesion area error indicates higher accuracy in lesion delineation by the automatic segmentation method.

The Pearson correlation coefficient is a statistical measure used to assess the linear relationship between two variables. In this context, it quantifies the degree of correlation between the lesion areas obtained from automatic segmentation and manual segmentation. A Pearson correlation coefficient close to 1 indicates a strong positive correlation, implying that the automatic segmentation results closely align with the manual segmentation results. Conversely, a coefficient closer to 0 suggests a weaker correlation.

Overall, the study's findings demonstrate the effectiveness of the multi-scale U-Net deep network model in accurately segmenting ischemic stroke lesions from non-enhanced CT scans. The incorporation of the Dice loss function addresses data imbalance issues, while the comparison between manual and automatic segmentation methods provides validation of the model's performance. The lesion area error and Pearson correlation coefficient serve as quantitative measures to evaluate the accuracy and correlation of the automatic segmentation results with manual segmentation, further validating the model's utility in clinical practice.

2.2.2 Deep Neural Network (DNN)

Cheon et al. conducted a comparative study evaluating the effectiveness of Deep Neural Networks (DNN) in predicting stroke risk factors compared to five other machine-learning methods. The analysis involved 11 variables, encompassing factors such as gender, age, type of insurance, admission model, need for brain surgery, geographical region, length of hospital stays, hospital location, number of hospital beds, stroke type, and others. With a dataset comprising 15,099 subjects with a history of stroke, the researchers employed a combination of DNN and scaled Principal Component Analysis (PCA) to automatically extract features from the data and identify stroke risk factors. The primary methodology employed deep neural networks to analyze the relevant variables, enhancing continuous inputs through scaled principal component analysis. This innovative approach yielded three key performance metrics: sensitivities, specificities, and Area Under the Curve (AUC) values. Sensitivity represents the proportion of true positive cases correctly identified by the model, indicating its ability to detect stroke cases accurately. Specificity measures the proportion of true negative cases correctly identified by the model, highlighting its capacity to correctly identify non-stroke cases. AUC, or the Area Under the Receiver Operating Characteristic Curve, provides a comprehensive assessment of the model's discriminative ability across various thresholds, with higher values indicating better overall performance in distinguishing between stroke and non-stroke cases. The reported values for sensitivities, specificities, and AUC were 64.32%, 85.56%, and 83.48% (Cheon, 2019), respectively. These results suggest that the DNN-based approach, supplemented by scaled PCA, demonstrates promising potential for predicting stroke and other diseases even when faced with limited data. The relatively high specificity indicates a low rate of false positives, while the AUC value reflects the model's overall predictive accuracy, underscoring its utility in clinical settings for identifying individuals at risk of stroke.

2.2.3 Generative Adversarial Networks (GNN)

Van Voorst et al. employed a method based on Graph Neural Networks (GNN) with the aim of developing and evaluating its effectiveness in segmenting infarct and hemorrhagic stroke lesions on follow-up Noncontrast Computed Tomography (NCCT) scans. The paper utilized data from three Dutch acute ischemic stroke trials, comprising 820 patients with baseline and follow-up NCCT scans. Employing a GNN, the researchers automated the segmentation of infarct lesions from follow-up scans in acute ischemic stroke patients. The results showcased moderate to good performance in lesion segmentation, as evidenced by Dice similarity coefficients ranging from 0.31 to 0.59 (Van, Voorst). Notably, infarct lesions observed at the 1-week follow-up exhibited excellent volumetric correspondence. This unsupervised approach holds promise for automated lesion segmentation in clinical settings. Noncontrast Computed Tomography (NCCT) scans, utilized for follow-up assessments, provide detailed images without the need for contrast agents, making them a valuable tool in stroke diagnosis and monitoring.

3 DISCUSSIONS

Several major challenges are on the horizon in machine learning for brain stroke prediction. First, interpretability remains a major obstacle, as many machine learning models are seen as esoteric black boxes, making it challenging to understand their decision-making mechanisms and placing significant design pressure on decision-makers. Then it is also very difficult to convince users and patients of the reliability of the results. Therefore, it is necessary to design for greater interpretability for decision-makers and users. Second, privacy issues arise when training models use personal sensitive data, raising concerns about the potential exposure of users' private information. In addition, the practicality of implementing machine learning models in real-world situations may be hindered by various factors such as data quality issues, sparse labelling, or environmental changes. Moreover, as models become more complex, interpreting their predictions becomes more challenging. Data quality and bias can significantly affect the performance and robustness of machine learning models, especially when faced with unbalanced datasets or missing data. Sometimes, data cannot be consistently achieved in machine learning models. After changing scenarios or missing some labels, obtaining the same data results and accurately predicting outcomes becomes challenging. Summarizing the necessary information and achieving uniform results for diverse datasets presents a significant challenge.

Looking ahead, potential solutions and avenues for progress are emerging, for example, the Shapley Addition Method of Interpretation (SHAP) approach, designed as a novel and cutting-edge method, aims to facilitate clinical interpretation and intuitive comprehension of feature significance. It accomplishes this by visualizing the relationship between each feature and its associated predictive power (Lundberg, 2020). The Federated Learning (FL) approach provides a way to train models on distributed data sources, improving model performance while protecting user privacy. A wide range of architectures based on Federated Learning, as mentioned in (Yaqoob, 2023), have been categorised as horizontal FL and vertical FL, and many people have used diverse approaches to outline the characteristics and results of some of the optimisation strategies implemented by FL and to discuss some of the expected business consequences of federated learning. In addition, using the principles of transfer learning, pre-trained models can be migrated from one domain to another of interest, thereby reducing data requirements and enhancing model generalisation. comprehensively look to compare and contrast several of the most widely applicable machine learning methods, using a combination of SHAP and FL to improve interpretability and privacy and achieve optimal solutions.

4 CONCLUSIONS

This work comprehensively discusses and compares the advantages and disadvantages between various traditional machine learning and deep learning on the prediction of stroke in patients, obtaining the method with the highest accuracy, and summarising the relatively well-developed dataset available for experiments. This paper mainly uses methods such as RF, GB, and U-Net for screening to generate targeted stroke prediction results synthetically. Some new techniques have not been considered in this article, such as large language models, time series models, multimodal data fusion, and causal inference methods, which will be added in the future to form a more complete system for more thorough consideration.

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