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Current critical review on prediction stroke using machine learning

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ABSTRACT

Strokes are a significant health problem because they often lead to long-term disabilities due to delayed diagnoses and insufficient information about the disease. The use of artificial intelligence (AI), specifically machine learning (ML) and deep learning (DL), has the potential to aid in stroke diagnosis and significantly advance healthcare. This review article critically examines predictive methods for ischemic and hemorrhagic strokes. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) method was used to identify 79 relevant articles from five databases spanning 2012 to 2022, with IEEE having the highest number of articles and citations. China had the most authors, and the random forest (RF) algorithm showed the most accurate results. A taxonomy categorizing the implementation and usage of ML and DL for stroke prediction was created and includes five focus areas: building, system planning, evaluation, comparison, and analysis. Additional research into other disease features related to stroke is warranted. Decentralized federated learning should also be implemented to collect data from remote locations for early diagnosis and create a single training model.

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1. INTRODUCTION

Stroke is a significant burden in developing countries, leading to increased mortality rates in Asia, Europe, and the Americas. Healthcare providers face challenges disseminating information about stroke, which can delay treatment [1]–[3]. Early diagnosis is critical to prevent stroke and optimize treatment outcomes [4]–[6]. Artificial intelligence (AI) methods, particularly machine learning (ML) and deep learning (DL), are crucial in reducing the incidence of stroke [7], [8].

Several researchers [9]–[12] incorporated various variables and observations into a predictive framework without pre-programmed rules, potentially increasing interest in using ML to predict stroke outcomes. ML offers an alternative for large-scale [13] and multi-institutional data and can optimize the selection process for endovascular treatment versus medical treatment in managing acute stroke [14]. Research conducted by Singh and Choundhary [15] describes an integrated ML and data mining approach to build predictive models, identifying new potential factors for stroke [16].

Comparing different methods for stroke prediction on datasets using decision trees (DT) [17], principal component analysis [18], and artificial neural network (ANN) classification algorithms has resulted in more accurate classification models [19]. However, the traditional medical personnel approach to predicting stroke must include identification [20], and effective methods are needed to reduce this impact [21]. In addition, data imbalance between classes in a dataset can affect prediction bias and degrade model performance [22]. Applying data-driven [23] and model-driven methods can improve their performance by training the data to be better [24].

A systematic literature review concluded that several ML and DL models have been developed to solve stroke cases. Such as predicting stroke-related mortality [25] and patient dependence on stroke care [26]. However, over the past few decades, classifying some of these studies has similarities in reviewing each classification methodically [27]. There are also few meeting basic reporting standards for clinical prediction tools, and no models available in a way that can be used or evaluated [28]. In addition, factor assessment is also crucial in addressing the issues surrounding the transparency of ML to find its reliability and dependability that can help in the forward trajectory of modern diagnosis [28]. Therefore, there should be more reviews in the literature that explain modeling techniques while also assisting readers in comprehending the many aspects of risk models and how to interpret them.

To provide reporting guidelines for clinical prediction tools, the systematic review study aimed to categorize the objectives of previous studies. These categories are model building, system planning with models, comparison of prediction model results, analysis of model applicability, and evaluation of the best model. These categories will be examples of advanced ML and DL procedures characterized by previous researchers in selecting the best model [29]. In addition, it can support formal and methodical ML and DL algorithms, system design and implementation, and responsible ML and DL practice [30]. It makes it easier to understand the technologies used in the ML development cycle and the differences between ML and DL programming and development [31]. Thus, it facilitates the comparison and selection of appropriate commercial products to support the lifecycle of ML and DL [32].

Because of this, we propose a practical taxonomy through five categories based on the objectives of previous researchers. The taxonomy serves to develop AI methods and identify the most effective algorithms to implement [33], [34]. In addition, the taxonomy results can help health services accelerate the stroke diagnosis process and help researchers identify features that are influential in stroke prediction.

This research addresses two critical issues: choosing an algorithm model that is easy to implement in healthcare and utilizing algorithms that significantly impact stroke prediction, especially for two types of stroke, resulting in optimal accuracy. Section 2 describes the information retrieval process used in this article. The findings and discussion will review the implementation methodology, including a taxonomy based on the methods shown in section 3. Finally, in section 4, the article concludes with conclusions and suggestions for future research topics.

2. METHOD

This study employed a systematic review protocol to investigate research inquiries concerning the utilization of ML in stroke prediction. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) procedure was employed to analyze previously published articles, identifying many works encompassing AI and its subdomains, including ML and DL, about stroke prediction [35], [36]. The search database encompasses vital information for implementing ML in stroke prediction. The investigation utilized five renowned databases that facilitated straightforward and intricate queries: Scopus, ScienceDirect, Springer, PubMed, and the IEEE Xplore digital library.

The research selection process involved two iterative rounds. The first step involved researching conference articles on the survey issue, which are important sources of recent and cutting-edge research. The second iteration involved in-depth examination of published articles that have undergone peer review and cover a wider variety of research [37]. This thorough review procedure provided researchers with a solid awareness of the research landscape, enabling them to expand on prior knowledge and reach insightful conclusions. The study findings are current and grounded on previous research, ensuring the reliability and credibility of the research and enabling thorough evaluations of survey issues.

The PRISMA approach is used in this research procedure to identify relevant publications, consisting of four steps: identification, screening, eligibility, and inclusion criteria [37]. The main research areas identified are stroke prediction, disease prediction, and classification using ML and DL [38]. The identification process involves expanding the main keyword through several steps to retrieve articles from five databases: Scopus, ScienceDirect, Springer, PubMed, and IEEE Xplore.

The study was conducted on February 16, 2022, using search boxes in various databases. The search procedure involved entering keywords like “stroke”, “AI”, “ML”, and “DL” and spanning from 2012 to 2023. The results from Scopus, ScienceDirect, Springer, PubMed, and IEEE totaled 1515 articles. The review process involved filtering out duplicate titles, resulting in 1110 articles. The feasibility assessment evaluated title, abstract, methods, results, and discussion of all papers, resulting in 270 remained.

In the Figure 1 showing, step was to review full-text articles, which led to 191 papers being inaccessible due to paywalls, restricted access, or unavailable sources. Ultimately, 79 papers were successfully sought after and extensively examined, providing a comprehensive overview of the research environment. The analysis focuses on the remaining 79 papers, providing a comprehensive understanding of the research environment.

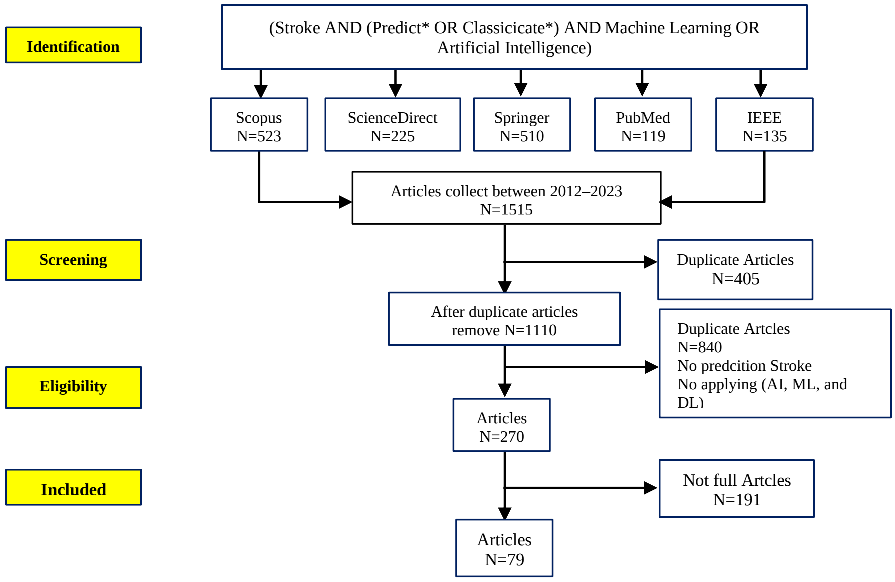

Figure 1. Selection process using the PRISMA method

3. RESULTS AND DISCUSSION

A study retrieved 1515 articles from five databases from 2012-2022, focusing on relevant research articles. 79 articles were selected for analysis, and a thorough text analysis was conducted. Improved classification was used, and indicators and constructive criticism were discovered. The study demonstrates the use of terminology such as summary tables, targets, verification criteria, descriptions, source indexes, and data sets to preserve relevant data. A summarised graph was developed, displaying source indexes, research distribution by nation, countries receiving the most citations, and the best algorithm used in publications.

3.1. Result by source indexes, nationality, most citation database, article by country, and best algorithm

Figure 2 illustrates the characteristics of the reviewed articles based on the following criteria: i) the database sources used in this review (Figure 2(a)), ii) the nationality of the first author (Figure 2(b)), iii) the number of citations by database source (Figure 2(c)), iv) the number of citations by country (Figure 2(d)), and v) the best accuracy of the algorithms for predicting stroke occurences (Figure 2(a)). The graph in Figure 2(a) displays the distribution of full-text articles used in the study, highlighting the importance of various databases. The graph shows that 32% of the articles were sourced from IEEE Xplore, 24% from ScienceDirect, and 23% from Springer. Scopus contributed 15% of published publications, while PubMed contributed 6%. The graph highlights the importance of IEEE Xplore, ScienceDirect, and Springer in the study's research goals. IEEE accounts for 32% of the 79 published papers, with a 25.5% share of the total articles PubMed aa, on the other hand, contributes slightly, accounting for 6% of the articles, due to its focus on health research and fewer topics related to AI in healthcare.

The study analyzed stroke prediction research articles from 23 different countries, revealing a significant body of work. China conducted the most studies, with 22 articles, followed by India with 12 papers, South Korea with 9, and the USA with 7. Bangladesh and Taiwan each conducted four studies, while 5 countries conducted 2 studies each, Australia, Germany, Indonesia, Malaysia, and Spain. The remaining eleven nations conducted one study each, highlighting the global nature of stroke research and the collaborative efforts of researchers from different backgrounds. The graphs in Figure 2(b) provide valuable insights into the global nature of stroke research and the collaborative efforts of researchers from diverse backgrounds.

The text analyzes the distribution of citations in stroke prediction research articles across various databases and countries, revealing the critical contributions of PubMed, IEEE, ScienceDirect, Springer, Scopus, and IEEE in advancing knowledge in the field. The highest number of citations is received by IEEE, with 25 articles specifically focused on stroke prediction accumulating 952 citations. ScienceDirect has the highest number of citations, with 579 citations from 19 research papers. Springer's database has 387 citations from 18 papers, while Scopus has 246 citations. Finally, PubMed has 5 studies about stroke prediction, generating 75 citations.

Figure 2. Graph results from 79 articles for: (a) publication database, (b) distribution articles by nationality, (c) most citation by source database, (d) most citation by nationality, and (e) best accuracy using algorthm for prediction stroke

The graph shows China has the most citations, with 405 citations from 22 articles, highlighting the significant contributions made by Chinese researchers in the field of stroke prediction. The text also emphasizes the need for more citations from articles addressing stroke prediction in Portugal, the author's homeland, as researchers and academic institutions still need to contribute to the body of knowledge on stroke prediction to be cited. Furthermore, Figure 2 displays the distribution of citations from various nations, with China having the most citations overall. Portugal, the author's country, has yet to receive any citations in the field of stroke prediction, distinguishing it from countries like China that have made notable contributions in terms of citations.

This article presents a graph comparing the accuracy of stroke prediction algorithms in published studies. The graph shows that the random forest (RF) algorithm is the most accurate, with twenty studies indicating its strong performance and widespread use in the scholarly community. Deep neural network (DNN) is also mentioned, with eleven articles utilizing it for stroke prediction. XGBoost (XGB) is another noteworthy algorithm, linked to ten articles. The graph highlights the contributions of ANN and support vector machine (SVM) algorithms to precise stroke prediction. DT and logistic regression (LR) algorithms are also highlighted, with six papers for each algorithm linked. The convolutional neural network (CNN) algorithm is mentioned, but more study or use in stroke prediction may be required. Naive Bayes (NB) and gradient boosting (GB) algorithms are also mentioned, along with Bayesian networks (BN), neural networks (NN), and multilayer neural networks (MNN). The graph provides an invaluable resource for understanding the efficacy and applicability of various stroke prediction algorithms.

3.2. Taxonomy literature review of research stroke prediction

This taxonomy was developed after analyzing 79 kinds of literature on stroke prediction and organizing methodological strategies from essential ML to advanced DL methodologies. Based on Figure 3, the 79 articles are divided into 2 main research objectives: development and approach. These 2 main objectives applied ML and DL methods, addressing stroke cases, such as ischemic and hemorrhagic. The specific objectives conducted by the researchers are further categorized into five: building, system planning, comparison, and analysis. Then, of the 79, we divided based on these categories, such as building with a total of 15 articles, system planning with a total of 13 articles, evaluation with a total of 13 articles, comparison with a total of 23 articles, and finally, analysis with 15 articles.

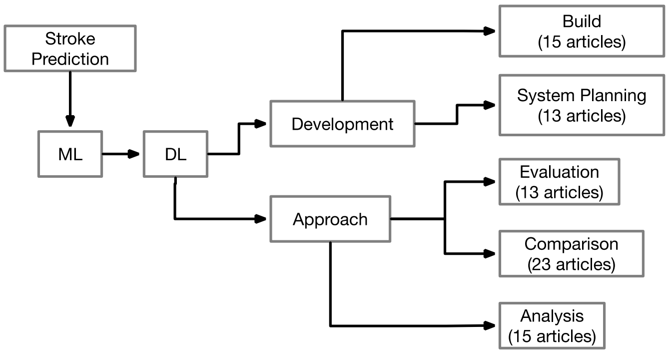

Figure 3. Taxonomy literature review of research stroke prediction

Furthermore, from the 79 articles divided based on these categories, we searched by selecting the model with the best performance in predicting stroke disease. As a result, we found that two articles have achieved 99% accuracy by implementing the RF algorithm in the model building category. Then, in modeling intelligent systems, one article uses the XGB algorithm, which gives comparable results to RF. Furthermore, in the primary objective section, namely approach, there is a focus on the objectives of previous research involving model evaluation, found one article using RF with 97% accuracy results. In addition, there is a comparison; out of 23 articles, only the model with DNN shows 99% accuracy. Then, in the analysis section, the highest accuracy achieved was 98% using MNN. For more details see in Table 1.

Based on Table 1 [39]–[44], of the 5 studies conducted, only three have applied datasets from the Kaggle database that produce the best performance. However, it needs to be shown for the features that are best used. In addition, the following study used very little data, only 79, but had many features and promising performance results. The last study applied image data. Namely, the results of CT scans on patients. From this research, there are areas for improvement in its application. Namely, the features used need to be maximized, and the selection of algorithms needs to be appropriate. Using a more suitable ANN algorithm would be better, but from these shortcomings, the results are excellent, namely, 97% accuracy. We will explain the two main objectives in full in the next section.

3.3. Development for stroke prediction

The research findings are visually displayed in Figure 3, which shows the taxonomy created using the two-step technique. The taxonomy is divided into two main branches, namely development and approach, to provide an overarching framework for organizing and understanding the research findings. In this section, we will describe the development model in this taxonomy shown in the development branch, as shown in Table 1, using various stroke cases. To build their prediction systems or applications, researchers examined various stroke cases to understand the variables influencing stroke prediction. Two articles used various models to develop their prediction systems or apps using data from Kaggle "stroke prediction dataset" [45]. These studies likely used different algorithms, techniques, or combinations to improve stroke prediction models.

Table 1. Summary articles from aim development and approach in stroke prediction using ML and DL

No	Aim to research	Study	Key features	Advantage	Limitations	Method	Best accuracy (%)
Development							
1	Build	[39]	Kaggle, 62,001 data, 12 feature	Utilize smoking status features to improve accuracy	Not all features are applied to all models	RF	99
2	System planning	[40]	Kaggle, 10,000 data, 12 feature	Improving the main algorithm for best performance	The comparison algorithm is better in performance than the main algorithm	XGB	99
Approach							
3	Comparison	[41]	Kaggle, 43,400 data, 12 feature	Improving the performance of the main algorithm with ant lion optimizer (ALO) and resampling	The results do not represent the true accuracy and will be biased due to the unbalanced dataset.	DNN	99.8
4	Analysis	[42]	Goldberger [43],79 data, 59 feature	Maximizing neural network model for feature fusion is then built to realize feature fusion of structured data and streaming data.	The dataset used is not maximized so that it is not known what features are suitable for implementation.	MNN	98
5	Evaluation	[44]	RSCM Indonesia, 92 data, 22 feature	Updating the detection of ischemic stroke with image data, namely CT scans of patients.	The implementation only uses the RF algorithm, but the result is no change in the density of the image data.	RF	97

Additionally, this taxonomy highlights the number of datasets researchers use to achieve optimal results. Understanding how important it is to combine different datasets, these studies aimed to minimize bias and ensure the reliability of the findings. One study by Stier *et al.* [46] applied the DL method and used 25 image files. The study's findings showed that applying the CNN algorithm can produce an accuracy value of 85%.

In contrast to previous studies, another study by Zhao *et al.* [47] focused on building a model to predict the risk of acute stroke. However, it should be noted that these two studies differed in the amount and type of data used, yet the findings from Zhao *et al.* [47] showed high accuracy. In addition, studies using ML suggest that using a sample size of less than 100 data points is appropriate [48].

However, this is particularly challenging in the case of post-stroke cognitive impairment due to the difficulty in collecting data for such studies. In addition, three studies using the same data produced models with different accuracy results. These models were then applied to build medical applications [49] and create early detection systems by implementing improvised algorithms [50]. In addition, application prototypes were developed based on symptoms or characteristics. Our latest finding is a study utilizing primary medical history data to develop a stroke risk prediction application [44].

Two studies used all available approaches and ML as the primary development model for building stroke prediction systems in the next branch of system roles. The results show that certain studies focused on building stroke prediction systems. His research focused on various variables and feature scales to assess stroke severity in patients over 65 years of age [51], and this research also utilized physiological characteristics, which can be combined with ML to create a compelling and adaptive system [52]. We have found from all our studies that ML can be used to create such a system. Doctors and clinical staff can perform fast and effective detection thanks to this method.

3.4. Approach for stroke prediction

Applications in predicting stroke can be divided into evaluation, comparison, and analysis. This division was made based on the review, and the research gaps are highlighted in Figure 3, which shows the relationship between stroke prediction and evaluation modeling studies. The relationship can be seen in Table 1, with eleven articles involving ML and four articles involving DL. The evaluation of the three studies showed that DL was more dominant, mainly due to the use of image data to achieve higher accuracy. In contrast, despite using more datasets than both, the ML implementation resulted in values that were far below [52].

Our findings show that the choice of algorithm used in a model impacts the results obtained. Moreover, when the same algorithm is used with slight variations, the difference in results is only about

2% [53]. This article compares different models used in research focusing on stroke prediction. This research paper includes a comprehensive collection of fifteen studies that used various statistical techniques and methods, supplemented by additional approaches. These studies aim to investigate and analyze various phenomena using a powerful combination of quantitative analysis and innovative methodologies.

Incorporating various statistical techniques underscores the researchers commitment to using rigorous analytical tools. These techniques may include descriptive statistics, inferential statistics, regression analysis, hypothesis testing, and data mining. Using these methods, researchers can extract meaningful insights from data, identify patterns, establish correlations, and draw accurate conclusions. This diverse and integrated approach increases the strength of their findings, deepens our understanding of research issues, and contributes to progress in the health sector.

The findings in this study are presented, specifically focusing on the different features and methods compared to previous ML models and approaches. Similar case studies from previous research used datasets with less than 100 entries. Remarkably, the outcomes of the present investigation exceeded those of the prior research [54]. Moreover, our subsequent findings regarding data quantity revealed studies with larger datasets, albeit with a 10% difference in accuracy [55]. Another case study by Cheng *et al.* [54] used image data as a predictor, yielding different results based on the specific database.

However, both studies produced the same average value. In addition, we also found comparisons between NN algorithms and other algorithms, especially those using ML methods. Six studies using the same dataset produced different results, but the four best algorithms, including NNs with different algorithm types, produced an average score of 80% [44], [56]–[60]. The other two studies using RF and LR algorithms achieved 97% and 81%, respectively, making the ratio of NN to RF the highest.

Furthermore, further findings involve the comparison of various algorithms combined with statistical methods and techniques such as synthetic minority oversampling technique (SMOTE), Chi-Square, feature selection, principal component analysis (PCA), partial least squares (PLS) optimization hybrids, and Cox models [13], [15], [24], [55], [61]–[63]. These studies provide valuable insights into the various modeling approaches and feature engineering methods used in stroke prediction research. Among the models and techniques studied, the reported performance ranges from a minimum of 70% to a maximum of 95%. As such, this explains that the evaluated algorithms and methodologies provide varying degrees of accuracy and predictive power in the context of stroke prediction. The specific values reported in each study reflect the effectiveness of the respective approaches in capturing and predicting stroke risk factors.

It is worth mentioning that one particular study cited by Gkantzios *et al.* [64] introduced apache spark as an additional comparative technique. This study introduced a novel approach that uses apache spark, a distributed computing framework, to improve the analysis and prediction of stroke events. By considering this alternative technique, the broader spectrum of comparative methods used in stroke prediction research is expanded, offering a unique perspective and potential insight into the predictive performance of the apache spark framework. To summarize, subsequent findings in stroke prediction research involve comparisons of algorithms, statistical methods, and various techniques.

As highlighted in several studies, these include SMOTE, Chi-square, feature selection, PCA, hybrid PLS optimization, and Cox models. The reported performance of these models and techniques ranged from 70% to 95%, highlighting the variation in their predictive accuracy. Additionally, one study cited by Gkantzios *et al.* [64] stands out by using apache spark as an alternative comparison technique, adding a different perspective to stroke prediction research. To provide a summary, we will now look at model evaluation. Seven publications on various analytic methodologies have been found and are presented in Table 1 of stroke prediction. This work advances our knowledge of the subject and adds to the growing corpus of research on stroke risk assessment. The model evaluation used in this study reflects the commitment of researchers to thoroughly evaluate their performance by utilizing various analytical tools, such as ML algorithms, statistical models, and data fusion techniques [27]. The researchers wanted to create a robust and precise stroke prediction model that utilizes a large amount of data, extracts essential properties, and generates valuable insights to help anticipate stroke.

In addition, using multiple analysis techniques highlights the interdisciplinary nature of stroke prediction research. Researchers from various disciplines, including computer science, medicine, epidemiology, and biostatistics, work together to share experiences and explore new analytical stances [59]. The comprehensive understanding of stroke prediction fostered by this interdisciplinary approach enhances the validity of the model suggested in this study. Through this evaluation process, the scientific community can continue to hone and improve stroke prediction models, resulting in findings with greater accuracy and clinical utility [65]. These works demonstrate the dedication of researchers to carefully assess the performance of their models and improve the field of stroke prediction research. These studies aim to improve the accuracy and dependability of predictive models, which will ultimately aid patient treatment and stroke risk assessment.

This paper identifies 3 studies [66]–[68] that show RF as the best algorithm for analyzing stroke prediction models. These studies showed accuracy values of 98%, which strongly supports this claim. In addition, some models achieved similar levels of accuracy but differed in the data and algorithms used. However, it is essential to note that the study by Saminathan *et al.* [68] needs to explain the number of datasets used. This study only used 5 classification algorithms for stroke prediction.

In contrast, Table 1 shows different findings from the results reported in by Lin *et al.* [69], where accuracy values above 90% were achieved without any improvement. Therefore, it becomes crucial to compare this study's results with previous studies' findings. In addition, the study conducted by Dev *et al.* [70] yielded the lowest accuracy results. Although they used the DT model improvised with PCA, the data provided (29,072) still resulted in accuracy values below 80%.

4. CONCLUSION

Accurate results are essential for effective treatment planning and patient well-being. AI techniques essential to the healthcare system include ML and DL, which provide a variety of viewpoints. This study aims to understand the function of AI processes in stroke diagnosis and identify significant contributions to research outcomes. As a result, five categories have focused objectives from each study we reviewed. In addition, this study revealed that IEEE published the most articles and references on stroke disease prediction, with China being the most relevant country. RF algorithm modeling is the best algorithm to produce accurate values and can be compared with other algorithms to improve model improvisation.

ML and DL methods are commonly used in research, with 5 focus areas: development, system planning, evaluation, comparison, and analysis. Five articles achieved 97% to 99.8% accuracy, while only one used image data from CT-Scan. Applying both methods improved the efficiency and accuracy of model design based on the data used. These findings contribute to future researchers by understanding the focus of the objectives in the literature review of each article. In addition to understanding the optimal model for disease prediction and effective treatment, it enables health professionals to identify potential barriers and provide proactive interventions. Further research on other factors related to stroke disease, including decentralized, federated learning, is recommended to create an updated taxonomy as a unified training model to collect various stroke disease data, making it easier for future researchers to achieve the desired goals.

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