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ORIGINAL RESEARCH

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DEVELOPMENT OF MACHINE LEARNING MODEL FOR CHARACTERIZING STROKE IMAGES

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Abstract:
Introduction: Stroke occurs due to interrupted brain blood flow, leading to cell death. AI and computer vision aid diagnosis, prediction, and patient management. Technologies like CT, MRI, and PET enhance stroke assessment. However, ML-based stroke diagnosis is underexplored in developing countries, including Nigeria, with limited model comparisons.
Aim: To systematically review the existing machine learning models for stroke diagnosis, and identify their strengths and weaknesses.
Materials and Methods: A systematic review of 880 Google Scholar articles on Machine Learning and Stroke was conducted. After applying PRISMA criteria, 44 studies were selected.
Results: The search returned 880 articles. After screening and removal of duplicates, the number of articles was reduced to 489. Out of these 391 papers were excluded based on title, keywords and abstract, 391 relevant studies met the inclusion criteria, out of these 98 articles were eligible. 54 articles were excluded after further screening and 44 papers that met the criteria for inclusion were reviewed. We found that the most commonly used ML models were random forest (10 studies), support vector machine (6 studies), neural networks (24 studies), and logistic regression (4 studies). The accuracy of machine learning algorithms ranged from 0.58 to 0.97.
Conclusion: We discovered that there are increasing research efforts on Machine Learning Models and stroke prediction but with a very few studies done in developing countries. The performance of the existing machine learning models is good but can be improved upon. Major improvements and validations are required for stroke models' adoption into clinical practice. Our future plan is to develop a homemade machine learning model for stroke diagnosis.
Keywords: Machine Learning, Stroke, Artificial Intelligence, Diagnosis, Models

All co-authors agreed to have their names listed as authors.

1. INTRODUCTION

Stroke is a deadly disease. According to the survey of the World Health Organization (WHO), stroke is one of the leading cause of death in the world [1] . The unfortunate thing about the disease is the fact of its occurrence and permanent damages to its patients before diagnosis is done. [2].

Stroke has remained a leading cause of morbidity worldwide leaving up to 50% of its survivors chronically disabled with reduced health related quality of life and depression [2] Stroke is broadly classified into hemorrhagic and ischemic stroke.

Hemorrhagic strokes Ischemic stroke

Figure 1: Types of stroke

There are two major types of stroke viz Ischemic and Hemorrhagic. Ischemic stroke is similar to a heart attack, except it occurs in the blood vessels of the brain. Clots can form in the brain's blood vessels, in blood vessels leading to the brain, or even in blood vessels elsewhere in the body and then travel to the brain. These clots block blood flow to the brain's cells. Ischemic stroke can also occur when too much plaque (fatty deposits and cholesterol) clogs the brain's blood vessels.

The human brain is the center of the central nervous system and is responsible for regulating the body's actions and reactions. The brain is enclosed in a thick skull and suspended in a clear bodily liquid called cerebrospinal fluid (CSF) which acts as a buffer for the brain in case

of sudden jolts. CSF is mostly made up of white blood cells, enzymes and glucose. The brain can be described as being consisting of two major types of tissues, the gray matter and white matter. The gray matter tissues consist of neuronal cells, glial cells and capillaries and perform most of the brain functions. The white matter mainly consists of bundles of myelinated axons and connects the various gray matter areas of the brain.

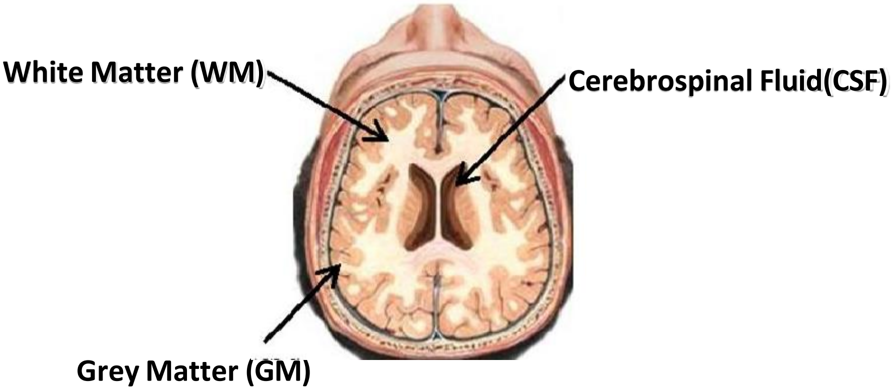

Figure 2: Image of the brain showing the three tissue classes

Visualizing the brain (Figure 2) using some imaging techniques can help in stroke prediction, diagnosis and patient management. Some of the many imaging technologies are Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT). A detailed history and imaging will usually exclude stroke mimics. It is recommended that a suspected stroke patient should have a brain Scan within 3 hours of symptom onset to allow for appropriate intervention to arrest progression of neurological deficits [3-5]. However, early stroke presentation in developing countries, within this limited time window is extremely difficult for several reasons ranging from poor stroke recognition, medics adoption of machine learning models to limited socioeconomic and infrastructural facilities.

Due to the substantial economic, social and medical problems stroke poses worldwide, there is a need to reduce its effects, by prompt institution of intensive management which has imaging diagnosis at its foundation and core.

Computational approaches have recently been applied to aid neurologist and other medical practitioners in decision-making. The healthcare business generates a lot of data regarding patients and disease diagnoses these days. These obtained data can be combined with computational tools to improve brain related disease diagnosis.

We set out to systematically review the existing machine learning models for cerebrovascular disease diagnosis, and identify their strengths and weaknesses. The knowledge of the existing ones will aid in the development of a robust computational system for stroke characterization.

2. MATERIAL AND METHODS

A systematic review [6] was adopted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The processes contained in the methodology are as follows

Study design, Search strategy and information sources and Study selection and data collection process.

This was a systematic review study which compared analysis of machine learning models for stroke diagnosis. We searched the Google Scholar database with emphasis on ML and stroke diagnosis using the terms; Stroke predictions, Machine learning, algorithm, etc. Titles and abstracts were screened for relevance. Inclusion and exclusion criteria were applied, Articles that met the inclusion and exclusion criteria were then downloaded and reviewed. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was used for publications' identification.

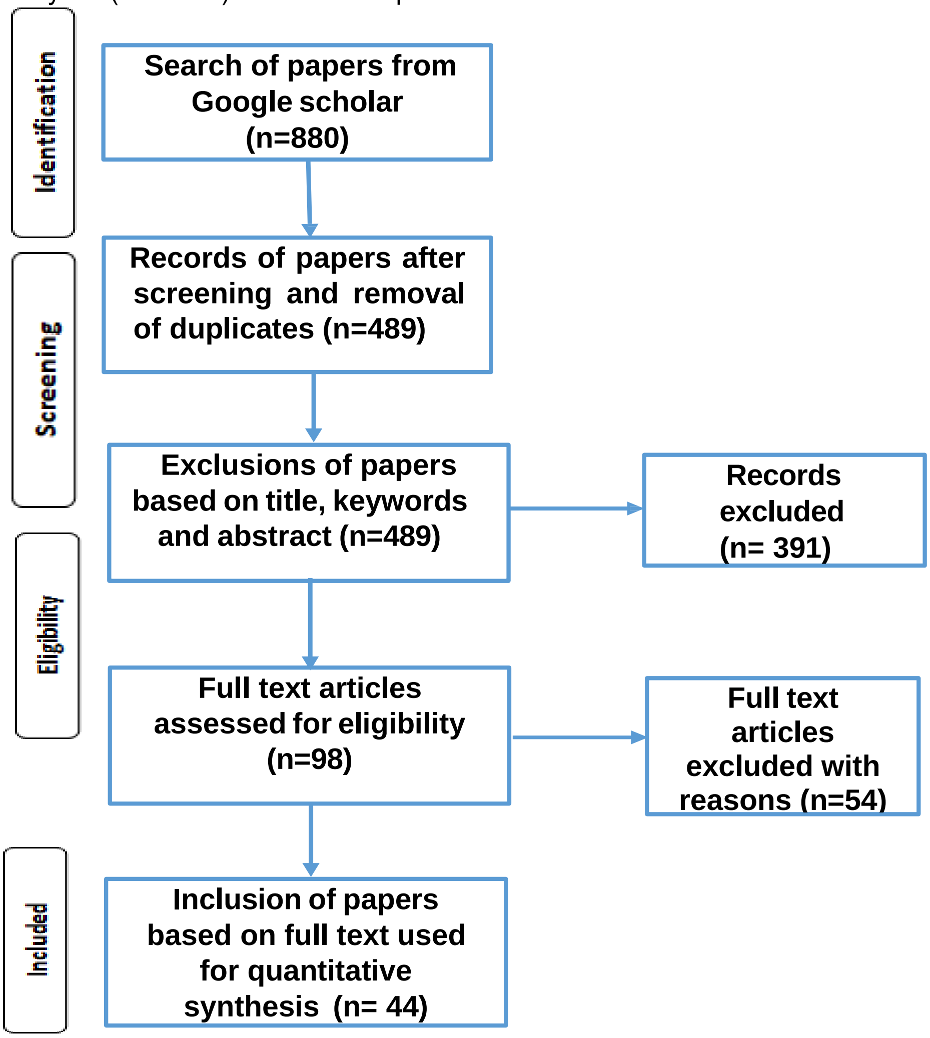

Figure 3: Systematic review results using PRISMA flow diagram

2.1 STUDY DESIGN, SEARCH STRATEGY AND INFORMATION SOURCES

Studies that contained machine learning algorithm in cerebrovascular disease prediction that met the required inclusion and exclusion criteria were systematically assessed, reviewed and carefully selected. The following are the components of the search strategy:

(a) Construct search terms identifying some essential keywords

(b) Determine alternative words for the keywords

(c) Establish exclusion criteria and derived the search term using Boolean operators

Result for (a) stroke diagnosis machine learning algorithms

Result for (b) stroke diagnosis machine learning algorithms characterization "magnetic resonance imaging" -Alzheimer -CT -cardiac -tumor –tumor

Result for (c) machine learning stroke model and algorithms stroke OR diagnosis "machine learning algorithms" -classification -heart -diabetes -engine -epilepsy -dementia -sport - treatment -children -Chinese -"Covid 19" -post-stroke -rehabilitation

The articles in this study were chosen from the Google Scholar database and were peer- reviewed. We reviewed strictly machine learning algorithm in cerebrovascular disease prediction using the search term constructed as “Results for (c)" and this became the final search term arrived at for these studies. Resources checked were journals, articles, and conference papers. Resources scrutinized were: conference proceedings, journal articles, book chapters and books.

2.2 Study selection and data collection process

For selection of articles in this study we used Preferred Reporting Item for Systematic Reviews and Meta-Analysis (PRISMA) to retrieve relevant journals, articles, books and conference papers. Articles were screened based on titles and studies were classified based on country of studies and the machine algorithm used. Inclusion and exclusion criteria were used to select the relevant articles to this study.

Electronic search was extensively performed in the Google Scholar databases up to year 2023 for studies on machine learning algorithm for stoke prediction or diagnosis.

2.2.1 Exclusion Criteria

Published articles were identified by searching the Google scholar database for all range in date to 2023. Non-English publications were excluded. Studies were excluded with the following reasons:

i. Stroke risk factors prevalence not explored
ii. Learning or Experiment procedures
iii. Incomplete or inappropriate study design, identified by studies without full information for determining inclusion
iv. Animal study
v. Diseases that are non- Cerebrovascular

The primary sources came from the results of studies identified based on the search terms and having constituent or semblance of keywords in any instance to this study. Selection was equally based on the publication evaluation quality. Evaluation of publication's quality was done on all types of stroke not to be biased on a particular type. Selection was also made based on title of the studies and abstracts.

The following data were extracted from each publication: title, author, reference, database, journal, methodology, target audience or population, publication quality description and year. Data classification was based on a number of performance metrics from the concluding publication sample. An in-depth review was carried-out in order to extract a list of categories to assist in the categorization of the performance metrics.

3. RESULTS AND DISCUSSION

3.0 Results

3.1 Literature Search

The final search term returned 880 articles. 880 potentially relevant studies were identified. After duplicates were removed, there remained 489 unique articles to review. We reviewed the titles and abstracts using the exclusion criteria and that led to the exclusion of 391 articles. We used the same criteria to review the full texts version of the remaining 98 articles out of which 54 articles were excluded and 44 articles were included for the studies.

3.2 Study Characteristics

The search result is presented in Figure 3 and Table 1. In summary, the search returned 880 articles. After screening and removal of duplicates, the number of articles were reduced to 489 out of these 98 articles were accessed for eligibility. 54 articles were excluded after further screening and 44 papers that met the criteria for inclusion were reviewed. We found that the most commonly used ML models were random forest (RF) 7 studies (15.1%), support vector machine (SVM) 3 studies (6.8%), neural networks (NN) 23 studies (52.3%), logistic regression (LR) 3 studies (6.8%), SVM/RF/NN 1 study(2.3%), SVM/RF/LR 4 studies (9.2%) and SVM/RF 3 studies(6.8%),. The accuracy of machine learning algorithms ranged from 0.58 to 0.97 (Table 1).

The years of publication of all relevant articles are from 2001 to 2023. Out of the 44 articles countries like France, New Zealand, Singapore, Greece, Korea, Egypt, Nigeria (1 study), Taiwan, Germany, Spain, Australia (2 studies), Canada (3 studies), UK, India (4 Studies), China (5 studies) and USA (13 studies). Table 1

Table 1: Distribution of existing research based on countries

S/N	COUNTRY	NO OF STUDIES	ARTICLE NUMBER	METHOD	ACCURACY
1	UK	4	[7-10]	NN/SVM	0.58 - 0.72
2	India	2	[11, 12]	RF/SVM	0.82, 0.95
3	Spain	2	[13, 14]	NN	0.8, 0.94
4	Taiwan	2	[15, 16]	SVM/NN/RF	0.78, 0.97
5	Singapore	1	[17]	RF/SVM	0.96
6	Germany	2	[18, 19]	NN/RF	0.68, 0.90
7	Canada	3	[20-22]	SVM/NN/RF	0.53 - 0.78
8	USA	13	[23-35]	SVM/NN/LR	0.65 – 0.96
9	South Korea	1	[36]	NN	0.91
10	Portugal	1	[37]	RF	0.77 – 0.81
11	Australia	2	[38, 39]	NN	0.71, 0.74
12	China	4	[40-43]	NN/RF	0.89 – 0.95
13	France	1	[44]	RF	0.80
14	Greece	1	[45]	NN	0.76
15	Korea	1	[46]	NN	0.89
16	New Zealand	1	[47]	LR	0.93
17	Switzerland	1	[48]	SVM	0.94
18	Egypt	1	[49]	NN	0.85
19	Nigeria	1	[50]	LR	0.97

3.3 Main Study Results

3.3.1 Taxonomy of Machine Learning Algorithm for Stroke Diagnosis

In this research, it was identified that the Machine learning algorithm proposed for the diagnosis of stroke were grouped into nine categories (4 main algorithms) and (5 combined algorithms) The four main algorithms are Neural Network (8 studies), Support Vector Machine (1 study), Logistic Regression (2 studies) and Random Forest (2 studies). The combined algorithms are SVM/NN/RF (5 studies), NN/RF (6 studies), SVM/RF (3 studies), SVM/NN/LR (13 studies) and SVM/NN (4 studies)

3.3.2 Knowledge extracted from existing Computational Techniques

The strengths and weaknesses of Machine learning algorithm for stroke diagnosis or prediction are presented as follows:

a) Neural Network

An analysis of the algorithms under this category shows the following:

Strengths: The advantages of the Neural network algorithms in these studies [13, 14, 36, 38, 39, 45, 46, 49] includes fast, reliable, and effective tool for characterizing the carotid plaque for early stroke risk stratification. Also useful for clinical assessment and timely identification of patients for treatment. Accuracy is much higher than the prediction result of other model.

Weaknesses: The problems with neural network in these studies [13, 14, 36, 38, 39, 45, 46, 49] are majorly, the time complexity to predict stroke in these algorithms were not highlighted. Also, some were suitable for early stroke only. It is prone to overlearning when the size of hidden neurons is too large and under learning when the number of hidden neurons is too small.

b) Support Vector Machine

Strengths: The advantages of the algorithms used in this study [48] is that SVM obtained the highest classification accuracy of 0.94 and a dice score of 0.95 for the classification of PACS, LACS and TACS images. That is, it works relatively well because of the clear margin of separation between classes. It is also more effective since the number of dimensions is greater than the number of samples. SVM is relatively memory efficient

Weaknesses: Disadvantages of SVM in the study is that having so few images limited the study to information extraction and assessment. It was only possible to extract information from the MRI images that can be used to differentiate the stroke severity. With more images higher accuracy is ascertained but SVM is suitable for small data.

c) Random Forest

Strengths: The advantages of Random Forest in these studies is that it can handle noisy data and outliers. It can handle both classification and regression problems and can work well with both categorical and continuous variables.

Weaknesses:

Random Forest can be less interpretable than a single decision tree because it involves multiple trees. It can be difficult to understand how the algorithm arrived at a particular prediction.

3.4 DISCUSSION

In this work, we reviewed all available articles related to machine learning algorithm for stroke diagnosis. This review was done to understand theoretical background of different algorithms and models developed to give an accurate measure in interpreting image analysis for quick and interpretation of brain stroke diagnoses.

For the purpose of classification, we classified algorithms into four main and five combined algorithms based on country of studies. We observed that ML algorithms have been demonstrated to have good potentials at predicting stroke using brain images, clinical and demographic factors. The mostly used ML algorithms are RF, LR, NN and SVM. We also observed that some studies used hybridized algorithm like SVM, RF and different categories of NN. Among the various algorithms reviewed, the most widely used is the NN. This is due to its ability to learn from data, arrange other algorithms, solve complex problems and makes decision reliable on its own. Neural networks have been used to model medical and functional outcomes of dangerous disease. They have become a popular tool for classification, as they are very flexible, not assuming any parametric form for distinguishing between categories of data.

The major strengths of this study are the critical and systematic review of existing studies. We used Google Scholar database because it is freely available worldwide and it is the biggest database for researched article. We equally ensured that the search terms were carefully and professionally conceptualized and defined. This help to identify strictly relevant articles. In addition, we utilized PRISMA in correctly applying our inclusion and exclusion criteria. This is globally acceptable standard of conducting and reviewing systematic review [51]. This confirms the conformity of our study with the good practice of systematic review.

One of the major limitations of this study is the use of only Google scholar database. It is inevitable that some useful articles might have missed out on some articles that are available on other database that are commercial.

4. CONCLUSION

In conclusion, we carried out a systematic review study of existing machine learning algorithm for diagnosis of stroke. We observed that the mostly used Machine learning algorithms for stroke prediction are Random Forest, Logistic Regression, Neural Network and Support Vector Machine. We discovered also that there are increasing research efforts on Machine Learning Models for stroke prediction. Major improvements and validations are required for stroke models' adoption into clinical practice. Our future plan is to develop a homemade machine learning model for stroke diagnosis.

AUTHORS’ CONTRIBUTIONS

OOO conducted literature review, performed experiments and wrote the first draft of the paper. BSA conceived and designed the study, supervised the entire work and wrote the final draft of the paper. MAR co-supervised the work and revised the final draft of the paper. All authors read and approved the final draft of the manuscript.

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