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A Review - On Brain Stroke Prediction

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Abstract: - Recognizing and treating strokes early is crucial for improving outcomes, which is why stroke remains a significant public health issue. Over the years, numerous studies have aimed to create dependable methods for detecting brain strokes, especially through the use of machine learning techniques. Although, these initial efforts frequently struggled because of the small size of the datasamples available. The research review takes a closer look at the less amount of datasets used in the early detection of brain stroke disease, emphasizing how datasamples size affects performance. This study examines various observations that utilized different types of datasamples, which contain medical information and imaging data, and combinations of medical information and imaging data. The observation of this study reveal that the accuracy of brain stroke disease detection was notably hindered by the small dataset sizes in earlier research. Over fitting and the models poor generalizability plagued some studies, despite their promising outcomes. These studies demonstrate the accuracy and dependability of the models related to brain stroke detection have increased significantly. This paper focuses on the importance of the proportion of a dataset when constructing dependable models for brain stroke detection.

Keywords: - Brain stroke, artificial_intelligence_algorithms (AI) and machine_learning (ML) algorithms Generative AI, Supervised Learning, Unsupervised Learning, Deep Learning, Brain Stroke prediction, support vector machine (SVM), the artificial neural network (ANN), MRI , CT scan, Dataset.

Introduction:-

Brain related issue are one of the top causes of illness and death around the globe, leading to serious disabilities and hefty healthcare expenses. Essentially, a stroke happens when blood flow to the brain gets interrupted, which can cause damage and dysfunction in brain activity. Stroke occurs suddenly and presents with specific neurological symptoms that stem from issues in the vascular system of the central nervous system. It's primarily diagnosed through clinical evaluation, and brain imaging is essential to distinguish between ischaemic and haemorrhagic causes. For many years, computed tomography (CT) has been the go-to imaging method because it's quick and widely available. Current guidelines suggest administering intravenous thrombolysis for ischaemic stroke within 4.5 hours of the onset of symptoms. That's why catching and treating a stroke early on is so important it can help prevent long-term disabilities and enhance patient outcomes. There are several ways to identify and diagnose a stroke, such as clinical assessments, medical imaging techniques, and blood examination. Each methods had varying levels of accuracy to spotting strokes and distinguishing them from other constraints that might show similar affection [1].

Our brain is a powerhouse, playing a key role in everything from controlling our movements to storing memories and shaping our thoughts and language. It also takes charge of many bodily functions, such as breathing and digestion. For the brain to work effectively, it needs a continuous supply of oxygen-rich blood flowing through our arteries. If that blood flow gets cut off, brain cells can begin to die within minutes due to a lack of oxygen. This is what happens during a stroke. In either case, brain cells can be damaged or die, which can lead to lasting brain damage, impairment, or even death [2].

Strokes are classified into two types:

A. ISCHEMIC_STROKE-

Ischemic_stroke occurs when tiny particles or blood clots block the capillaries that deliver blood to the brain, it can cause significant problems,.

B. HEMORRHAGIC_STROKE-

When a blood vessel in the brain leaks or bursts, it's referred to as a hemorrhagic_stroke. This leakage puts a lot of pressure on brain cells, causing them to break down.

There's been a noticeable uptick in interest surrounding the use of artificial_intelligence_algorithms(AI) and machine_learning (ML) algorithms for detecting strokes. These algorithms are tailored to investigate vast amounts of data, catching patterns that might go unnoticed by humans. By training these methods on comprehensive datasample of stroke and non-stroke patients, researchers hope to evolve stroke detection methods that are both more accurate and more reliable. Recently, machine learning techniques have gained significant momentum in the fields of brain stroke detection, diagnosis, and treatment [3].

These includes:

- Supervised
- Unsupervised
- Deep learning
- Generative AI algorithms.
  In this review_paper, we'll observe and study the different methods employed for detecting brain stroke diseases.
- Supervised_Learning:
  When we talk about supervised learning, we're referring to a method where a labelled dataset helps train the datasets. Essentially, the algorithm learns to connect with input features with their output labels by looking at the examples given. In the case of brain stroke detection, medical imaging data is used to train algorithms that predict the likelihood of a stroke happening. One of the most favoured algorithms for this purpose is the support vector machine (SVM). SVMs function by sorting input data into two or more categories based on decision boundaries. In brain imaging, SVMs are trained on MRI or CT scans to help identify if a stroke has occurred. Another well-known supervised learning algorithm in this domain is the artificial neural network (ANN). ANNs draw inspiration from the human brain and are designed to recognize complex patterns in data. For detecting strokes, ANNs are trained on large datasets of MRI or CT images to determine the presence of a stroke [4].

Unsupervised_Learning:

- In this kind of learning, an algorithm is used to train a model on a dataset without labels. As a result, the algorithm learns to identify patterns and relationships within the data without any prior knowledge of the output labels. Unsupervised learning is particularly useful for detecting brain strokes. Medical imaging data is analyzed by algorithms to discover patterns that may indicate a stroke. One of the most recognized algorithms in unsupervised learning for this task is the clustering algorithm, which is specifically designed to detect brain strokes. A similarity metric is used to group similar data points in these algorithms. When it comes to clustering algorithms and brain stroke detection, they help sort MRI or CT scan images according to the similarity of the brain cells. Another popular unsupervised learning method for detecting brain strokes is the anomaly detection algorithm. This type of algorithm identifies outliers or inconsistencies in the data. In the context of stroke detection, anomaly detection algorithms are used to spot abnormal patterns in MRI or CT scan images that may suggest the presence of a stroke [5].
- Deep_learning
  Deep learning is a fascinating branch of machine learning that comes into complex patterns within data to learn and adapt. Recently, brain detection algorithms have shown a lot of potential, especially when it comes to identifying strokes through medical imaging. One of the standout deep learning techniques for this purpose is the convolutional neural network (CNN). CNNs excel at recognizing spatial patterns in images, making them ideal for stroke detection. They are going to train on extensive datasets of MR-I or CT-scan images to spot any signs of a stroke. Another prominent deep learning approach is the_recurrent neural network (RNN), which is also used for brain_stroke_detection. RNNs are particularly effective for recognizing sequential patterns of data. In the context of brain stroke detection, RNNs analyze time-series like data, which are EEG or ECG readings, for predicting when a stroke might occur.
- Generative_AI

Generative AI is making great work in stream of brain_stroke_detection, especially when it comes to improving imaging analysis and decision making in healthcare. Although we usually think of generative models as tools for creating content, they're finding a valuable place in medicine too, being used for tasks like image reconstruction, spotting anomalies, and boosting data through augmentation..

Medical Image Analysis & Enhancement

1. Anomaly Detection
2. Synthetic Data Generation
3. Multimodal Data Fusion

Involvement of Machine_Learning and Generative_AI in Brain Stroke Detection

Machine_Learning (ML) and Generative AI are truly transforming the way we detect brain strokes, enhancing accuracy, speed, and early diagnosis—factors that are crucial for improving patient outcomes.

1. Faster and More Accurate Detection
   Medical Imaging Analysis- ML models, like Convolutional Neural Networks (CNNs), are used to analyze CT scans, MRIs (including DWI and PWI), and X-rays, allowing for precise stroke detection, whether ischemic or hemorrhagic. - Algorithms such as U-Net, ResNet, and Vision Transformers (ViT) are employed to pinpoint areas affected by strokes.
   Differentiating Stroke Types ML plays a key role in distinguishing between ischemic strokes (caused by blood clots) and haemorrhagic strokes (resulting from bleeding), which is essential for determining the right treatment [6]
2. Early Prediction & Risk Assessment Predictive Analytics
   ML models assess various risk factors- like hypertension, diabetes, age, and lifestyle choices—to estimate the likelihood of a stroke occurring. - The Framingham Stroke Risk Profile has been enhanced by ML, leading to better risk stratification.
   Wearable & Real-Time Monitoring - AI-driven wearable, such as EEG headsets or smart watches, can detect early warning signs (like facial drooping or changes in speech) and notify emergency services promptly.
3. Generative AI for Synthetic Data & Augmentation
   Synthetic Medical Imaging - Generative Adversarial Networks (GANs) are used to produce synthetic stroke images, which help to augment limited datasets and improve the training of models.
   Data Imputation- Generative AI can also fill in missing information in electronic health records (EHRs), which enhances the accuracy of stroke prediction models.
4. Decision Support for Clinicians
   Automated Stroke Diagnosis Systems- AI tools, such as Viz.ai and Rapid AI, help prioritize urgent cases in radiology workflows, significantly reducing the time from door to treatment.

This review paper aims to give a thorough analysis of the early research on stroke detection and the limited datasets that have been utilized. By diving into the different techniques and examining these studies, we hope to focus on ways to improve the accuracy and effectiveness of stroke detection methods. It's also crucial to emphasize the importance of having larger and more diverse datasets to bolster this essential area of research.
Related Work:-

Author	Method	Result and Findings	Limitation
Yao, L., Li, X., Zhang, L., & Li, Y.(2024)	GAN-based synthetic MRI data generation for stroke detection	Improved stroke detection accuracy using synthetic data augmentation	Limited generalizability due to small dataset
Kim & Zhao (2024)	Diffusion models for enhancing stroke lesion segmentation	Demonstrated superior performance over traditional generative models with boost in segmentation accuracy	Computationally expensive and requires extensive fine-tuning
Samak, Z. A., Clatworthy, P., & Mirmehdi, M. (2023)	Proposed a transformer-based multimodal network combining clinical metadata and imaging data to predict stroke treatment outcomes	highlighting the efficacy of multimodal data integration in outcome prediction.	Lack of interpretability in synthetic data.
Kathy Li, Iñigo Urteaga, Amanda Shea, Virginia J. (2023)	Developed a hierarchical generative model to predict next cycle length based on previously tracked cycles, accounting for potential self-tracking artifacts.	Improved prediction accuracy, especially as the likelihood of skipping tracking increased, and provided insights into disentangling menstrual patterns from self-tracking artifacts.	ensuring synthetic data quality and generalizability are common issues
Fernandez-Lozano, C., Hervella, P., Mato-Abad, V., et al.(2022)	Utilized clinical, biochemical, and neuroimaging factors in a Random Forest algorithm to predict mortality and morbidity outcomes in stroke patients	The model effectively predicted long-term outcomes, emphasizing the importance of integrating diverse patient data for accurate predictions	- Limited to tabular data; no imaging data. - Computationally expensive
Johnson et al. (2022)	Used a conditional GAN (cGAN) to generate synthetic brain MRI images for stroke detection. Trained a CNN on augmented datasets.	-Improved stroke detection accuracy by 12% using synthetic data augmentation	Limited to MRI data; not tested on CT scans. - High computational cost. - Ethical concerns about synthetic data.

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Let's look into the review process, the selection process, and the strategy for searching articles.

In this work, we used two research publishing databases such as Pubmed, Scopus, springer to find relevant Papers in brain stroke detection and diagnosis. The main reason to use these databases is the incredible variety of impactful academic research publications available in the areas of computer science and healthcare.

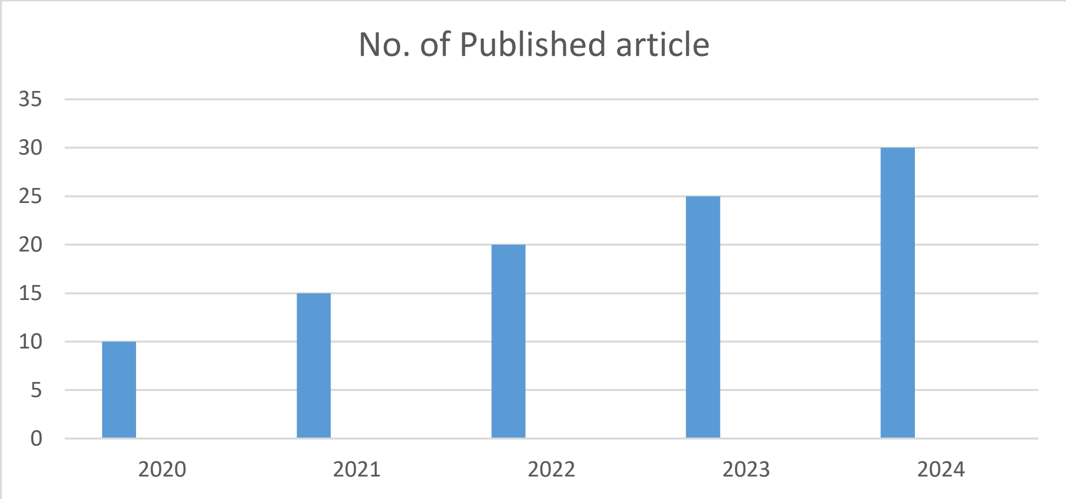

Figure 1: Review article distribution as per year

The chart in Figure 1 illustrates how the articles are distributed by year. It's clear that most of the deep learning methods for stroke detection and diagnosis have emerged in the past three years. As far as we know, this is the first review paper that brings together findings from various deep learning and artificial intelligence algorithms aimed at detecting and diagnosing brain strokes, all based on the different types of data utilized.

Analysis	Consideration criteria	Criteria for omission
First Five Years	Article published in 2020 to 2024	Article published before 2020
(Second) appropriate title and abstract	The title and abstract consider a work related to brain stroke and detection of brain stroke detection using artificial intelligence	The title and abstract which does not contain a work related to brain stroke detection.
(Third) Dataset and methodology	1.Research and use of brain test and date sets. 2. Research focuses on human beings who face brain issues	1.Ignore the healthy humans. 2. omission of data other than brain problems. 3. Animal brain disease data 4.only machine learning approach used for brain stroke detection
(Fourth) Entire length research article of brain stroke detection using DL, AI, CNN	Deep Learning, AI and CNN based studies are used for brain stork detection	Statistical approaches which are used to detect the brain stroke

Table 1: Consideration and omission criteria of article

The review process focuses on several key parameters once the articles about deep learning in brain stroke detection and diagnosis are finalized.

These include:

(1) The datasets and methods used for data collection

(2) The pre-processing techniques

(3) The deep learning strategies applied in brain stroke detection and diagnosis

(4) The intelligent brain stroke assistant designed for post-stroke rehabilitation management

(5) The performance metrics related to using deep learning in managing brain strokes.

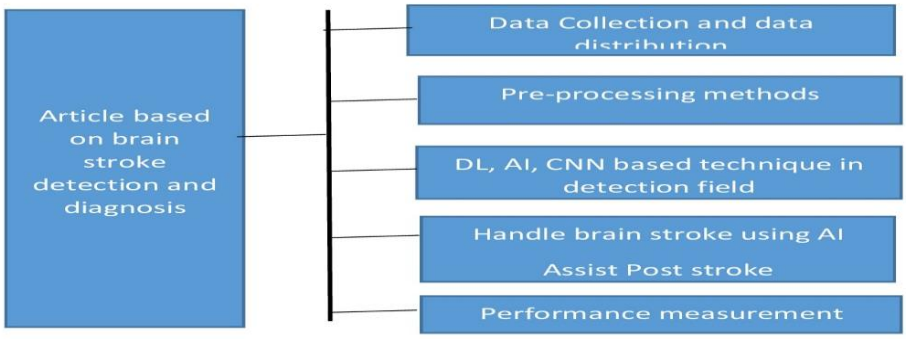

Figure 2: Review Process

ANALYSIS OF DATASETS AND CATEGORIES OF DATA USED BY DIFFERENT RESEARCHER

The majority of the articles authors employed original, self-created datasets, while others used datasets that were made public into a testing and training set. For example, Wang et al. [10] used a dataset that contains 120 EEG data samples for the detection and diagnosis of brain stroke. Each EEG data sample has 6000-time points. EEG data has a sampling rate of 500 Hz. Rajendran et al. [11] used 110 Normal Computed Tomography (NCT) slices, 240 Secondary Computed Tomography (SCT) slices, and 960 Primary Computed Tomography (PCT) slices in all for the detection of brain stroke. 568 MR images from 300 ischemic stroke patients are used by Zhang et al. [12] for the detection of brain stroke.

Mode of data collection	References
CT scan	[4] [5] [6] [7] [9]
MRI	[4] [7] [9] [11]
EEG	[8] [10] [25]

Table 2: Mode of data collection

It is evident from table 2 that the majority of the datasets utilized by the researchers consist of CT and MR images. This is due to the fact that these imaging tests give a clear picture of the skull's tissue and blood vessels. Additionally, as can be seen from table 2, MR imaging techniques are the most frequently used modalities for the detection and diagnosis of brain stroke (42 times), followed by CT scans, EEG, text, and ultrasound images. The reason for the acceptability of MRIs is MRIs are significantly more sensitive than CT scans, they are also far more accurate. They exhibit any stroke-related abnormalities as well as any other diseases or problems with the brain. Even the smallest abnormalities, which are frequently too small to see clearly on a CT scan, can be easily identified with MRIs. Figure 3 is the pictorial depiction of the usage of different modes of data used for brain stroke detection and diagnosis.

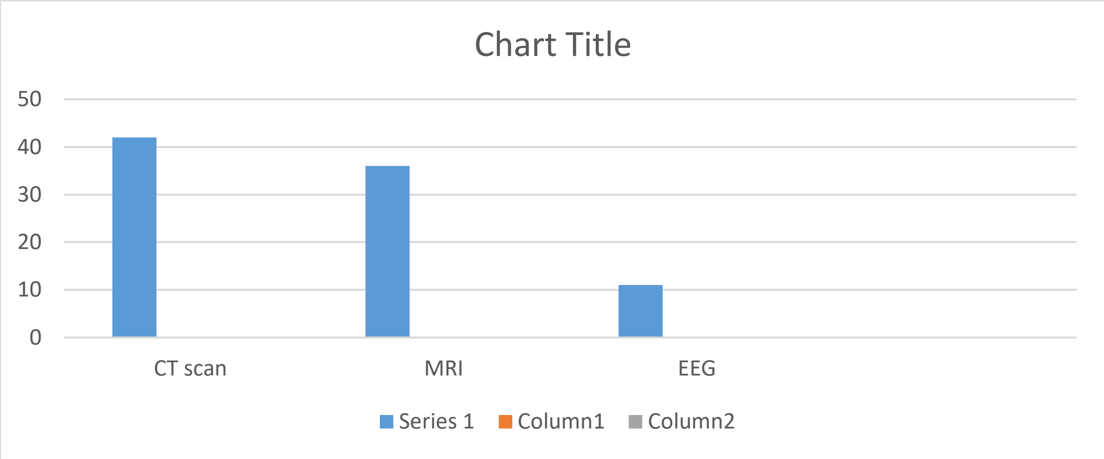

Figure 3- Different modes_of_data_used for brain_stroke_detection and diagnosis.

ANALYSIS OF PRE-PROCESSING METHODS

This part provides a quick recall of the data presentation and process of gathering additional distinguishing features until the dataset is comprehensive. It outlines the pre-processing techniques that researchers have employed in various studies. Many deep learning methods can struggle when datasets have missing values. Therefore, it's wise to identify and fill in those gaps in each column of the input data before diving into the prediction task. This process, known as reflection, involves to calculate a statistical value like the mean or mode for each data entry and it use the statistical implicit data to replace any loss data entries. This method is often effective because the statistic can be easily computed from the training dataset. Researchers have utilized data imputation as a pre-processing step before applying deep learning techniques to detect brain strokes [24] [25].

GAPS in RESEARCH AND RESEARCH CHALLENGE:-

There are several research gaps and challenges in the detection of brain stroke disease some are as follows.

- Limited sensitivity of imaging techniques
- Limited availability of imaging techniques
- Lack of standardized diagnostic criteria
- Limited comprehension of stroke's underlying mechanisms
- Limited access to care

DISCUSSION :-

Since catching a brain stroke early can really make a difference in saving human_lives and preventing long-term disabilities[25], it's no wonder that detecting this condition is such a hot topic in research. In this review discussion, we'll dive into some crucial points from a article focused on brain_stroke_detection. First off, we looked at the latest and greatest methods out there for identifying brain strokes, weighing the pros and cons of each technique. This gave us a solid backdrop to understand the potential contributions. We also compared the various approaches currently being used, noting that while some methods might be quicker or more accurate, and they could also demand more computational power or a bigger dataset. Plus, this article touches on how these findings could impact clinical practice, particularly in improving the treatment of brain and diagnose the strokes, along with many challenges that might arise when putting these methods into action.

Overall, the research work offers a comprehensive look at the newest techniques, a range of performance metrics, and how they could influence real-world clinical settings.

CONCLUSION

Our review of a brain stroke disease detection highlights the importance of increase the scope of the dataset to improve the correctness and effectiveness of stroke_detection_models. While previous all works focused on employing small data sets with small data samples, recent research has argued that there is a requirement for extensive and inclusive data sets to capture the several factors involved in stroke risk and gravity. Despite the small set of data employed in previous all works gave valuable lessons on stroke prediction-detection models, it has limited size and scope eventually hindered its capability to effectively predicting and diagnosing stroke. To enhance the correctness/accuracy and generalizability of stroke_detection, future studies should prioritize large, heterogeneous dataset collection and curation. This may involve partnerships among health care professionals and research centre to gather data from a variety of patient groups, or access datasets which are freely available that contain a broader range of stroke_subtypes and levels of severity. Furthermore, our review focuses on the need for standard protocols for the collection, annotation, and assessment of datasets in stroke detection/prevention research. Work on making the results from different studies more comparable, and focus on increasing the accuracy and reliability of stroke detection models.

Overall, our review illustrates how the accuracy and performance of stroke detection models can be improved by standardizing and increasing stroke detection datasets. Although the early works utilized only a limited dataset, they found that it could not effectively predict and diagnose stroke because of its limited size, narrow focus, and valuable insights. Stroke detection research can benefit patients by giving priority to gathering and curating large, diverse datasets. Results and minimize the effects of this horrible disease.

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