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A Comprehensive Review on Earlier Detection of Brain Cerebral Hemorrhage Stroke And Alzheimer's Disease Using Artificial Intelligence

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Abstract

Early detection of brain Cerebral Hemorrhage Stroke is of critical importance in medical imagery. It reviews the application of advanced learning algorithms to increase the accuracy and efficiency of brain stroke detection using noninvasive imaging (in particular MRI). In the last couple of years, recent machine learning and deep learning approaches like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and hybrid models have shown an overnight progress by automating the process of extraction, segmentation, and classification of brain tumors. Early symptoms of Alzheimer's dementia include: Memory impairment, such as trouble remembering events. Having a hard time concentrating, planning or problem-solving. Trouble finishing daily tasks at home or at work, such as writing or using eating utensils. You can't do. If another treatable condition is causing memory loss, your healthcare team can start treatments. For those with Alzheimer's dementia, starting medicines early can help slow the decline in memory and other cognitive skills.

Keywords: *Convolution neural network, Brain Cerebral Hemorrhage, Alzheimer's, MRI Image, SVM*

1. Introduction

Neurological disorders, such as cerebral hemorrhage, stroke, and Alzheimer's disease, are a significant global health burden. Early detection and diagnosis are crucial for improving patient outcomes, treatment effectiveness, and overall quality of life. Advancements in Artificial Intelligence (AI) have opened new avenues for early detection and diagnosis of these conditions. AI techniques, such as machine learning, deep learning, natural language processing, and computer vision, can analyze large datasets, enabling healthcare professionals to detect signs of disease at earlier stages. This review examines AI applications in medical imaging, genetic profiling, clinical decision support systems, and predictive modeling for these conditions. It also discusses the challenges and limitations of AI in these domains, as well as potential future directions for AI in improving diagnostic accuracy, facilitating personalized treatment strategies, and enhancing patient outcomes. This review aims to provide a comprehensive overview of the role of AI in the early detection of cerebral hemorrhage, stroke, and Alzheimer's disease. The paper will examine current AI applications in medical imaging (such as MRI, CT scans, and PET scans), genetic profiling, clinical decision support systems, and predictive modeling for these conditions. It will also highlight the challenges and limitations of AI in these domains, including data quality, interpret-ability, and integration into clinical practice.

1.1 Problem Statement

Alzheimer's is defined as irreversible, progressive brain disorder that slowly destroys memory and thinking skills and eventually the ability to carry out the simplest tasks. In existing work limited with Alzheimer's are irreversible, effort on daily activities, high memory loss and reducing the size of brain etc. Previous works focused on 2D and 3D images formats to detect but we considering 4D images for earlier detection because there is no cure for Alzheimer's disease but we prevent it by earlier detection. [1-10]

1.2 Motivation

To identify the efficient solution to detect Alzheimer's disease which cannot be cured but delayed by early detection using various techniques such as brain imaging and graph theory. We include machine learning techniques to automate this process and find out efficiency. Besides graph theory has been utilized as an efficient tool in diagnosing Alzheimer's and in finding the developed differences in the brain as the result of the disease.

2. Literature survey

This review is so important to the field because it will provide the opportunity to consolidate knowledge, bring attention to advancements and challenges, act as a guide for future research, and provide concrete improvements in the clinical application of advanced learning algorithms in the detection of brain tumors. It can result in better, more efficient, more equitable solutions for patients suffering from brain cerebral hemorrhage stroke and Alzheimer's disease. Gupta R, Krishnam SP, Schaefer PW, Lev MH, Gilberto GR (2020) an east coast perspective on artificial intelligence and machine learning: part 1: hemorrhagic stroke imaging and triage. Neuroimaging Clin N Am 30(4):459466. https://doi.org/10.1016/j.nic.2020.07.005 (Epub 2020 Sep 17. PMID: 33038996)Heit JJ, Coelho H, Lima FO et al (2021) Automated cerebral hemorrhage detection using RAPID. AJNR Am J Neuroradiol 42(2):273–278. S. Al-Shoukry, T. H. Rassem, N. M. Makbol Alzheimer's diseases detection by using deep learning algorithms: A mini-review IEEE Access, 8 (2020), pp. 77131-77141. Overall, on the basis of high-level literature review, we found that the published papers in this area tend to focus on two main areas of research, namely, biomarkers and neuro imaging, but with increasing interest in image analysisT. Liu, W. Fan, C. Wu. A hybrid machine learning approach to cerebral stroke prediction based on imbalanced medical dataset Artificial Intelligence in Medicine, 101 (2019), p. 101723 .This paper presents a hybrid machine learning approach to predict cerebral stroke for clinical diagnosis using incomplete and class imbalanced physiological data. The approach uses random forest regression and automated hyper parameter optimization on a 43,400-record medical dataset. The results are also cost-effective. K Mouridsen Detection of early infarction signs with machine learning-based diagnosis by means of the Alberta Stroke Program Early CT score. M Din · 2023 · Cited by 37 — Early aneurysm identification, aided by automated systems, may improve patient outcomes. Therefore, a systematic review and meta-analysis of the diagnostic accuracy of artificial intelligence (AI) algorithms in detecting cerebral aneurysms using CT, MRI or DSA was performed.

2.1 Diagnosis of Alzheimer's Disease

Alzheimer's is a disease that worsens the dementia symptoms over several years (Zebene et al. 2019). During its early stage, it affects memory loss, but in the end, it loses the ability to carry the conservation and respond to the environment. Usyal et al. (2020) decided on the analysis of dementia in Alzheimer's through investigating neuron pictures. They utilized the Alzheimer's disease neuro imaging initiative convention that comprises T1 weighted magnetic resonance information for finding. The prescient shows the precision estimated the characterization models, affect-ability, and explicitness esteem. Ljubic et al. (2020) presented the method to diagnose Alzheimer's disease from electronic medical record (EMR) data. The results acquired showed the accuracy by 90% on using the SCRL dataset. Soundarya et al. (2020) proposed the methodology in which description of shrink brain tissue is used for the ancient analysis of Alzheimer's disease. They have implemented various machine and deep learning algorithms. The deep algorithm has been considered the better solution provider to recognize the ailment at its primary stage with reasonable accuracy. Park et al. (2020) used a vast range of organizational health data to test the chance of machine learning models to expect the outlook occurrence of Alzheimer's disease. Lin et al. (2019) proposed a method that used the spectrogram features extracted from speech data to identify Alzheimer's disease. The system used the voice data collected via the internet of things (IoT) and transmitted to the cloud server where the original data is stored. The received data is used for training the model to identify the Alzheimer's disease symptoms. As seen in Fig. 4, (Subasi 2020) proposed a broad framework for detecting Alzheimer's illness using AI methods. The learning process is the process of optimizing model parameters using a training dataset or prior practice. Learning models can be predictive, predicting the future, descriptive, collecting data from input data sources, and combining them. Two critical stages are performed in machine learning and deep learning: pre-processing the vast input and improving the model. The second phase involves effectively testing the learning model and resembling the answer. Oh et al. (2019) offered a technique for demonstrating the end-to-end learning of four binary classification problems using a volumetric convolutional neural network form. The trials are performed on the ADNI database, and the results indicated that the suggested technique obtained an accuracy of 86.60% and a precision of 73.95%, respectively. Raza et al. (2019) proposed a unique AI-based examination and observation of Alzheimer's disorder. The analysis results appeared at 82% improvement in contrast with notable existing procedures. Stroke and cerebrovascular disease detection AI can analyze and detect stroke signs in medical images as if the system suspects a stroke in the patient. It immediately gives the signal to the patient or doctor. Researchers have proposed various methodologies to showcase the impact of AI in stroke and cerebrovascular detection (Singh et al. 2009). O'Connell et al. (2017) assessed the diagnostic capability and temporal stability for the detection of stroke. They observed the mostly identical patterns between the stroke patients and controls across the ten patients. They achieved the specificity and sensitivity of 90% across the research. Labovitz et al. (2017) stated the use of AI for daily monitoring of patients for the identification and medication. They achieved the improvement by 50%on plasma drug concentration levels Abedi et al. (2020) also presented a framework to build up the decision support system using an artificial neural network, which improved patient care and outcome. Singh et al. (2009) compared the different methods to predict stroke on the cardiovascular health study dataset. They also used the decision tree algorithm for the feature selection process, principal component analysis to reduce the classification algorithm's dimension, and a back propagation neural network. Biswas et al. (2020) introduced an AI-based system for the location and estimation of carotid plaque as carotid intima-media thickness for the same and solid atherosclerotic carotid divider discovery and plaque estimations. [11-20]

3. Methodology

Alzheimer's is defined as irreversible, progressive brain disorder that slowly destroys memory and thinking skills and eventually the ability to carry out the simplest tasks. In existing work limited with Alzheimer's are irreversible, effort on daily activities, high memory loss and reducing the size of brain etc. Previous works focused on 2D and 3D images formats to detect but us considering 4D images for earlier detection because there is no cure for Alzheimer's disease but we prevent it by earlier detection.

3.1 Cerebral Venous System

Physiological regulation and pathological changes of cerebral venous flow. Left: Two main mechanisms participate in the physiological regulation of cerebral venous blood flow. A passive mechanism is mediated by pressure differences and an active one is regulated by sympathetic nervous system. Right: When cerebral venous drainage is impaired, ISF fails to be discharged and aggregates in the brain tissue, leading to brain edema. At the meantime, BBB is disrupted and inflammatory response is stimulated. These three basic pathological processes form a vicious cycle, causing damage to the brain tissue. In addition, hemorrhagic events and venous collaterals formation could also be observed following cerebral venous drainage impairment. Figure 1 shows Cerebral Venous System.

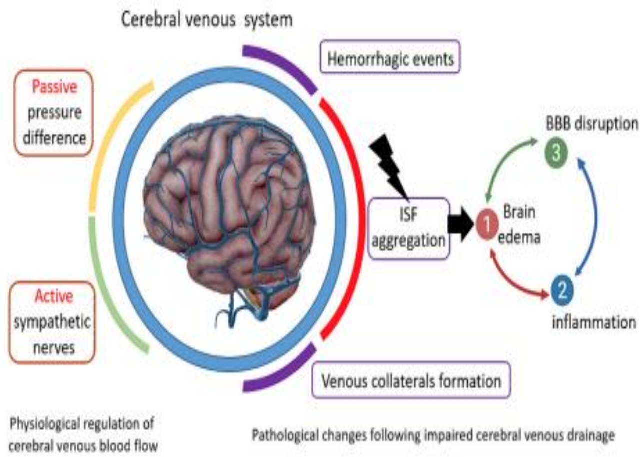

Figure 1 Cerebral Venous System

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3.2 Pathological Events Following Impairment of Cerebral Venous Outflow

Pathological events following impairment of cerebral venous outflow. Both thrombosis/thromboembolism and extra vascular compression are capable of impairing cerebral venous outflow. The impairment leads to an increase in intravascular pressure, resulting in numerous pathological processes, which are shown in the figure. CSF, cerebrospinal fluid; BBB, blood-brain barrier; MMP-9, matrix metallo proteinase-9. Figure 2 shows Pathological Events Following Impairment of Cerebral Venous Outflow assessed the diagnostic capability and temporal stability for the detection of stroke. They observed the mostly identical patterns between the stroke patients and controls across the ten patients. Resembling the answer. Oh et al. offered a technique for demonstrating the end-to-end learning of four

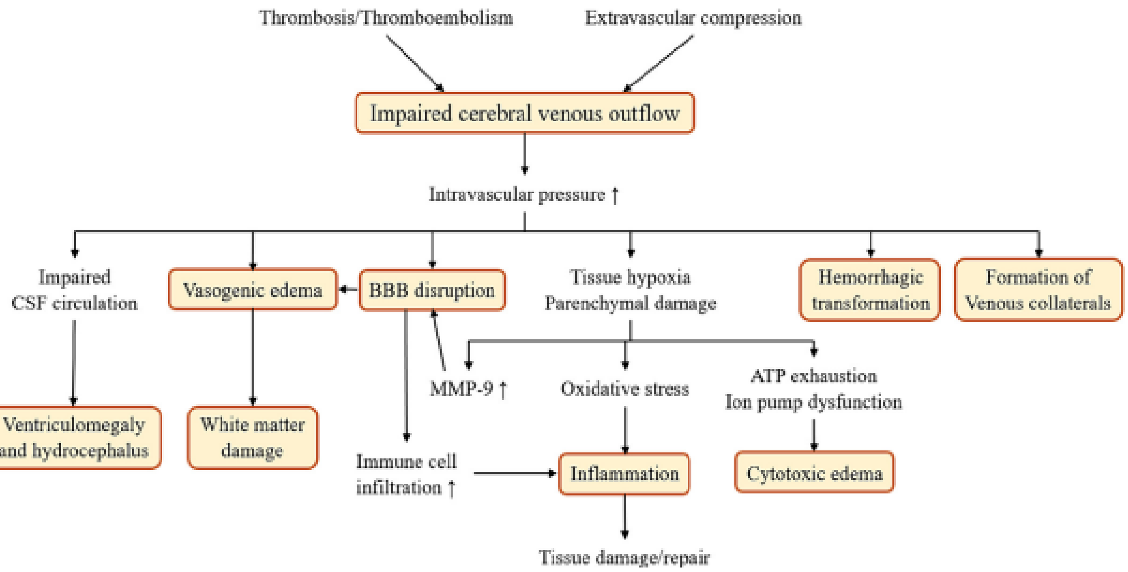

Figure 2 **Pathological Events Following Impairment of Cerebral Venous Outflow**

4. Research Gaps

It is crucial to identify research gaps in the domain of earlier detection of brain cerebral hemorrhage stroke and Alzheimer's disease through artificial intelligence using advance learning algorithms in order to guide future research and methodology. Here are several key research gaps in this area:

4.1 Stroke and Hemorrhage Detection in Real-Time

- **Real-Time, Accurate Diagnosis**: Stroke and cerebral hemorrhage detection often relies on imaging technologies like CT or MRI, but interpreting these images in real-time, especially during critical windows, remains difficult. Hemorrhagic strokes, in particular, can be subtle and may require high sensitivity for early detection.
- **Gap**: Developing AI models that can accurately detect strokes or cerebral hemorrhages in real-time, even from low-resolution or non-contrast imaging (e.g., from ambulances or remote sites), is a major challenge. [21-30]

4.2 Multi-Modal AI Models

- **Combining Different Data Modalities**: For complex diseases like stroke or Alzheimer's, AI models that can integrate and analyze multi-modal data (e.g., imaging, genetic, demographic, and clinical data) could significantly enhance early detection.
- **Gap**: Development of multi-modal AI frameworks that integrate various data types (e.g., genomics, MRI, PET scans, cognitive tests) to improve the diagnostic process, particularly for Alzheimer's and hemorrhagic strokes.

4.3 Ethical and Privacy Concerns

- **Bias, Privacy, and Security**: AI models, especially those based on large datasets, can be prone to biases, particularly when data is not representative. Additionally, privacy and data security concerns are particularly significant when handling sensitive medical information.
- **Gap**: Addressing issues related to data privacy, security, and bias in AI-based healthcare systems, while ensuring compliance with medical ethics and regulations (e.g., HIPAA, GDPR).

4.4 Integration with Existing Clinical Workflows

- **Seamless Integration into Practice**: AI models for stroke, hemorrhage, and Alzheimer's detection need to be integrated seamlessly into existing healthcare workflows. This involves overcoming technical challenges such as compatibility with different Electronic Health Record (EHR) systems, medical imaging technologies (e.g., MRI, CT), and real-time decision support systems.
- **Gap**: Research should focus on developing models that can easily integrate into clinical workflows, providing real-time alerts or diagnostic support without disrupting daily practices.

4.5 Interpret-ability and Explain-ability

- **Black-box Nature of AI Models**: Many AI algorithms, especially deep learning models, are often seen as "black boxes." In clinical settings, healthcare professionals need to understand not just the prediction but also how the AI arrived at that decision. [30-37]
- **Gap**: There is a significant need for improving the inter predictability and explain-ability of AI models in healthcare. This includes providing clinicians with actionable insights and visualizations to support clinical decision-making.

5. Performance Analysis

Several key performance indicators are used when evaluating various machine learning (ML) and deep learning (DL) models for tumor identification (for instance, for categorization of MRI images). Other important specifications and these metrics each assess a different aspect of performance for the model, such as accuracy, precision and recall. An overview of the commonly used performance evaluation metrics can be found below.

Accuracy

$$Accuracy = \frac{TP + TN}{Total\ instances}$$

Sensitivity (Recall)

$$Sensitivity = \frac{TP}{FN + TP}$$

Specificity

$$Specificity = \frac{TN}{FP + TN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

F1 Score

$$F1Score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity}$$

Mean Squared Error (MSE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Predicted - Actual)^2$$

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Predicted - Actual|$$

Dice Coefficient (Dice Similarity Index)

$$Dice\ Coffi cient = \frac{2 \times |A \cap B|}{|A| + |B|}$$

Jaccard Index (Intersection over Union)

$$Jaccard\ Index = \frac{|A \cap B|}{|A \cup B|}$$

5.1 4D functional Magnetic

New approach to functional magnetic resonance imaging (FMRI) data analysis. The main difference lies in the view of what comprises an observation.

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Here we treat the data from one scanning session (comprising t volumes, say) as one observation. This is contrary to the conventional way of looking at the data where each session is treated as t different observations. Thus instead of viewing the v voxels comprising the 3D volume of the brain as the variables, we suggest the usage of the vt hypervoxels comprising the 4D volume of the brain-over-session as the variables. A linear model is fitted to the 4D volumes originating from different sessions. Parameter estimation and hypothesis testing in this model can be performed with standard techniques. The hypothesis testing generates 4D statistical images (SIs) to which any relevant test statistic can be applied. In this paper we describe two test statistics, one voxel based and one cluster based, that can be used to test a range of hypotheses.

6. Acknowledgement

Would like to express my sincere gratitude to all those who have contributed to the development of this kind research on the earlier detection of brain cerebral hemorrhage, stroke, and Alzheimer's disease through artificial intelligence. Firstly, I would like to thank the research community for their continuous advancements in both artificial intelligence and neurodegenerative disease detection, which have inspired and shaped this study. The efforts of scientists, clinicians, and engineers in integrating AI with healthcare are invaluable and have provided the foundational knowledge necessary for this research.

Conclusion

Finally, implementing advanced learning algorithms in brain tumor detection problem presents a breakthrough in medical imaging and diagnosis research. Opportunities for improvements of diagnostic accuracy, reductions in time to analysis, and better patient outcomes exist by integration of machine learning and deep learning techniques. These review have resulted in various methodologies and technique used in the detection of brain tumors by processed technique, feature extraction and model selection and evaluation. However, there are still some important challenges to overcome, such as a lack of large annotated data set, generalization across different patient populations, and incorporation of multi-modal data. In addition, explainable AI is yet to play an essential role, as clinicians need to trust and understand the rationale behind the automated predictions to then be likely to adopt them in practice.

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