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A Survey on Deep Learning Approaches for Brain Stroke Classification

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Abstract - Brain Stroke is one of the leading causes of death, where timely and accurate diagnosis determines patient outcomes. CT scan is considered a standard imaging technique used in the diagnosis of acute stroke because of its fast imaging, widespread use, and distinction between hemorrhagic and ischemic strokes. However, manual interpretation of CT scans demands considerable clinical expertise and is Susceptible to differences between observers, particularly under time-critical conditions. With rapid evolution of artificial intelligence, deep learning (DL) approaches including Convolutional Neural Networks (CNNs), attention-based mechanisms, Vision Transformers (ViTs), and ensemble methods have showed remarkable potential in automating brain stroke classification from CT images. Specifically, this survey focuses on a systematic review of twelve studies on brain stroke CT image classification, with an emphasis on the architecture, data sets, pre-processing, training process, and performance measures. Moreover, this paper identifies the limitations of current models, including class imbalance, few labeled data, high computational costs, and low interpretability. Furthermore, important research gaps and future directions are discussed.

Keywords: Brain Stroke, Computed Tomography, Deep Learning, Convolutional Neural Networks, Medical Image Classification, Hemorrhagic Stroke, Ischemic Stroke.

I. INTRODUCTION

Brain stroke, also be called as a cerebrovascular accident (CVA), when the blood supply is interrupted due to either blockage is referred as ischemic stroke and rupture of blood vessels is referred as hemorrhagic stroke. Brain stroke is one of the major causes of death across the world and a major contributor to neurological disabilities. There are many stroke incidences reported from low and middle-income countries, since the regions lack advanced medical facilities that can help with the disease management. As brain damage occurs quickly following the onset of a stroke, prompt diagnosis becomes critical. The importance of rapid diagnosis can be captured in the saying, “time is brain.”

CT scan technology is the widely used method for the diagnosis of stroke since it is quick, easily accessible, and relatively cheap. Non-enhanced CT scans are very useful in diagnosing hemorrhagic strokes that are visible on CT images due to the presence of bright spots caused by blood. Conversely, the detection of ischemic strokes is quite difficult due to minor changes in tissue density.

Previously, ML techniques like Support Vector Machines and Random Forests were commonly employed for stroke detection. These models used manually designed features, including texture, intensity, and shape characteristics. Although they achieved reasonable results, their dependence on handcrafted features limited their ability to generalize across different datasets and imaging conditions. The introduction of DL, particularly in Convolutional Neural Networks, the performance is significantly improved by enabling automatic feature extraction directly from images. Over time, more advanced architectures like ResNet, VGGNet, DenseNet, EfficientNet, and Vision Transformers (ViTs) have been applied to medical imaging tasks, leading to further improvements in accuracy. More recently, hybrid models combining CNNs with attention mechanisms and transformer-based designs have gained attention for their ability to capture both local and global image features.

In previous works on stroke detection, the researchers mainly relied on classic ML algorithms such as Support Vector Machine and Random Forest. These models involved using manually crafted features, which include texture, intensity, and shape features. While their performance was quite satisfactory, the models suffered because they depended on manually crafted features, meaning that their generalizability was low. However, when deep learning came into the picture and Convolutional Neural Networks became the primary models in image analysis, things started changing, and performance greatly improved. With the development of models such as ResNet, VGGNet, DenseNet, EfficientNet, and Vision Transformers (ViT), there have been even more

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improvements in model performances, with many people now focusing on hybrid models of convolutional neural networks and attention mechanisms. However, there are still several challenges in developing robust deep learning models for stroke classification. For instance, the datasets tend to be imbalanced, meaning that there are fewer stroke examples compared to normal examples. There are also imbalances between various types of strokes. The number of labeled data in clinical settings is very small, and it limits our ability to use deep learning models.

Moreover, in real-time deployment during emergencies, there must be accuracy and computational efficiency of the model.

The current review discusses twelve critical studies ranging from 2022 to 2026 which are dedicated to the topic of classifying brain strokes through CT scans. These papers explore diverse techniques such as CNN, attention-based architectures, vision transformers, ensembles, and hybrid models. The papers are analyzed based on methodology, data used, results achieved, advantages, and disadvantages. Research gaps are then determined from this analysis, and possible future directions are outlined. This paper is structured as follows: Section II presents related literature, Section III identifies research gaps, and Section IV concludes the paper.

II. EXISTING WORK

1. Deep Learning Based Brain CT Image Classification with Hyperparameter Optimization through Transfer Learning for Stroke

Chen et al. (2022) [1] proposed CNN models, namely VGG-16 and ResNet-50, with transfer learning have been used for the classification of CT images into various classes, such as hemorrhage and infarction. In this study highlighted that proper hyperparameter tuning and sufficient dataset size significantly improve model performance, with ResNet-50 achieving high accuracy. In general, a CNN framework with a classification method can be applied in real-world applications because of its faster results than segmentation frameworks like U-Net. In addition, such strategies as transfer learning and data augmentation are beneficial for medical data, which usually lacks balance. Finally, optimization approaches like Adam help achieve better results. However, there are some significant weaknesses to this approach. For instance, a lack of transparency may be viewed as a major problem because of the black box approach that makes clinicians feel insecure. Moreover, such approaches are dependent on the availability of a sufficiently large, well-balanced dataset, which is hard to find in medicine. Furthermore, varying the image quality from other hospitals affects model performance.

2. A Deep Learning Approach for Detecting Stroke from Brain CT Images Using OzNet

The authors, Oznur Ozaltin et al. [2] presented a novel deep learning-based technique for stroke identification through brain CT scan data analysis, where a specially constructed CNN-based system (referred to as OzNet) was applied for binary classification tasks. For the purpose of boosting the efficiency of OzNet, the authors suggested constructing hybrid models that involve the combination of deep CNN with feature selection and conventional ML classifiers. In particular, the authors suggest applying such machine learning classifiers as Decision Tree, k-Nearest Neighbor, Linear Discriminant Analysis, Naïve Bayes, and Support Vector Machine on the basis of the features selected via the minimum Redundancy Maximum Relevance (mRMR) algorithm from OzNet-generated deep features. As it appears from the results of experiments described in the paper, the combination of OzNet, mRMR, and Naïve Bayes proved to be most effective, achieving 98.42% accuracy and 0.99 AUC value. Nevertheless, there are some limitations that should be considered, and one of the critical problems of this work is that the utilized data set is quite limited. Additionally, this technique utilizes a multi-stage process involving the processes of feature extraction, selection, and classification, thereby contributing to the increased complexity of the system. Moreover, the algorithm only performs binary classification and cannot be used for multiclass classification, such as diagnosing hemorrhagic and ischemic strokes. Lastly, just like most deep learning algorithms, this method is non-transparent, thus making it challenging for practitioners to trust the decision-making process. This research, therefore, illustrates that the use of deep learning techniques, in combination with machine learning methods, can result in improved stroke recognition, although improvements still need to be made.

3. End-to-End Vision Transformer Architecture for Brain Stroke Assessment Based on Multi-Slice Classification and Localization Using Computed Tomography

Ayoub et al. [3] have designed an advanced Vision Transformer (ViT) architecture optimized for the automated detection and localization of strokes based on brain CT images. The traditional approach to training vision transformers on independent image patches has been replaced by multi-slice aggregation in order to account for volumetric context through subsequent CT slices. In addition, the model is capable of performing stroke classification and localization tasks in a unified end-to-end framework. The experimental evaluation of the proposed method on clinical data obtained from different institutions has shown excellent results regarding stroke classification and superior localization accuracy in comparison to slice-based CNN models. The application of CT-specific positional encoding emerged as the most essential feature that allowed accurate multi-slice alignment.

Overall, the work can be considered as a significant contribution to volumetric reasoning for stroke detection using brain CT scans. The multi-task design is another advantage of the method since it provides localization maps along with classification results. However, the high computation burden associated with the transformer attention mechanism applied to dense CT volumes and lack of publicly available localization annotations remain the main limitations of the work.

4. Brain Stroke Classification Using CT Scans with Transformer-Based Models and Explainable AI

In the work of Shomukh Qari et al.[4] developed an innovative deep learning framework for multiclass stroke classification with CT scan image. Authors tested the transformers architectures such as Vision Transformer and its variations including MaxViT, Transformer -in -Transformer, and ConvNeXt in terms of efficiency in classification task with medical images. MaxViT in combination with data augmentation demonstrated the best results with the accuracy and F1-score of 98%. These results confirm the ability of the transformer architecture to learn spatial dependencies in the CT images. In order to increase the level of interpretability, the authors applied Explainable AI with Grad-CAM++. This method allows visualization of regions that affect the predictions. It enables increasing the level of trust of clinicians since medical reasoning can be aligned with the decisions of AI models. The authors used data augmentation technique that helped with solving the problem of class imbalance. Despite high performance, there are several limitations in the model. Firstly, the data comes from only one geographical area that limits the generalizability of the model to other populations. Secondly, transformer architectures need to use significant computational resources, which makes such models not efficient in low resource environment. Furthermore, although the Grad-CAM++ improves interpretability, which may not explain the internal decision making process completely of the complex transformer models. The system also relies only on CT images, without incorporate multimodal clinical data, which could further improve diagnostic accuracy.

5. Dual-Task Vision Transformer for Rapid and Accurate Intracerebral Hemorrhage CT Image Classification

Fan et al. [5] Another study conducted by Snekhalatha Umapathy et al. focused on developing a deep learning ensemble model to detect and classify various types of intracranial hemorrhages using brain CT scans. This deep learning ensemble model incorporated advanced neural network architectures, such as SE-ResNeXT and Long Short-Term Memory to extract both spatial and temporal information from the medical images. The research model used large datasets, namely RSNA brain CT hemorrhage dataset and CQ500 to classify various types of hemorrhages, such as epidural, subarachnoid, and subdural. In order to increase model interpretability, the researchers utilized Grad-CAM, which allowed highlighting the important features of CT images responsible for making classification decisions. Overall, the study reported extremely high accuracy of the proposed ensemble deep learning approach above 99%. Such results show how effective the use of the deep learning ensemble technique is when comparing with other standalone neural networks. The ensemble method adds to the complexity of the computations and may need a lot of processing power, thus reducing the capability to be used in real-time applications in environments where resources are limited. In addition, the model is mainly designed for 2D CT slices, but the use of 3D volumetric imaging may lead to more accurate diagnosis. Further, even though Grad-CAM contributes towards explaining the decision process of an AI, it might not provide complete explanation of how the complex ensemble model makes its decisions.

6. A Weighted Ensemble Approach with Multiple Pre-Trained Models for Brain Stroke Detection

Polat et al. [6] proposed the use of a weighted ensemble framework using six pre-trained CNN models, namely ResNet50, MobileNetV2, EfficientNetB2, VGG16, Xception, and DenseNet121, for brain stroke classification using CT images in a binary scenario. The individual model performance indicated that EfficientNetB2, Xception, and DenseNet121 outperformed other individual models with an accuracy exceeding 98%. The combination of three best models using weighted averaging technique yielded an ensemble accuracy of 99.84%, with respective F1-scores of 99.17% and 98.4% for stroke and normal classes. The weights were optimally set based on individual models validation performance. Ensemble method has demonstrated the advantage of using multiple feature sets from different architectures, resulting in enhanced accuracy compared to individual models. The proposed ensemble algorithm is highly desirable for clinical applications with high risk of false negative. Nevertheless, increased computational complexity limits its real-time application in emergency departments due to limited resources. Moreover, its binary classification capability cannot provide subtype-based guidance. [6] introduced a weighted ensemble strategy combining six pre-trained CNN architectures—ResNet50, MobileNetV2, EfficientNetB2, VGG16, Xception, and DenseNet121—for binary brain stroke detection from CT images. Individual model performance was first evaluated, revealing that EfficientNetB2, Xception, and DenseNet121 each surpassed 98% accuracy. A weighted average ensemble combining the three best-performing models achieved a remarkable overall accuracy of 99.84%, with F1-scores of 99.17% and 98.4% for stroke and normal classes, respectively. The weighting scheme was optimized based on individual model validation performance to maximize ensemble diversity while minimizing misclassification rates. The ensemble approach shows that combining complementary feature representations from diverse architectures consistently improves classification robustness over any single model. This methodology is well-suited for clinical deployment scenarios where false negatives carry significant risk. However, the ensemble increases inference computational cost, which may limit real-time deployment in resource constrained emergency settings. The binary classification scope also prevents subtype-specific clinical guidance.

7. Deep Learning-Driven Multi-Class Classification of Brain Strokes Using Computed Tomography

This retrospective bi-center study [7] has designed and validated two deep learning models utilizing Expanded ResNet101 network architecture for classification and scoring of stroke from CT images. The study used 8,186 CT images from 250 patients, where Model 01 was trained using 6,386 images for classification and Model 02 using 1,619 images for scoring. For Model 01, accuracy was 99.6%, precision was 99.4%, and F1-score was 99.6%, while Model 02 had corresponding values of 99.2%, 98.8%, and 99.1%, respectively. Independent validation was done by an expert radiologist and two different clinicians, who reported accuracy of 78.6% and 60.2% for Models 01 and 02, respectively.

The most important aspect of this study lies in its independent validation procedure that was carried out by expert clinical professionals. It provides a practical understanding of loss in accuracy when moving from a research laboratory to actual clinical practice. The difference in accuracy between internal and external validation accuracies, being nearly 20% lower in the latter case, shows the continuous struggle for domain generalization.

8. Stroke Detection in Brain CT Images Using Convolutional Neural Networks: Model Development, Optimization and Interpretability

Hassan Abdi et al.[8] suggested a CNN based framework for stroke detection in brain CT images while giving importance to interpretability and performance. This model was trained with 2501 CT images using data preprocessing methods including resizing, normalizing, and data augmentation. CNN model consisted of several convolutional layers and dense layers, which were tuned with hyperparameter optimization. The validation accuracy of 97.2% was achieved along with high precision and recall scores of 96%. To ensure clinical reliability, interpretability techniques like LIME, saliency maps, and occlusion sensitivity were implemented to visualize the important regions that contribute to the model's prediction. It was found that the model relies on clinically meaningful features in the CT image to predict accurately. Hence, this model is helpful in assisting radiologists during decision-making. Moreover, it possesses reasonable generalization capacity as it achieves 89.73% accuracy in predicting stroke in another dataset. Despite excellent accuracy, this method encounters certain limitations. The significant drop in the accuracy of the model when tested in external data suggests that it has poor generalization capability.

9. An Efficient Deep Learning Framework for Brain Stroke Diagnosis Using Computed Tomography Images

In an experiment conducted by Sabbir Hossen et al., a hybrid framework was proposed for brain stroke detection using CT images by adopting the combination of DL-based feature extraction and ML classifiers. In this experiment, multiple pre-trained Convolution Neural Networks such as MobileNetV2, DenseNet201, and ResNet50 have been used to perform deep feature extraction. Further, the extracted features have been improved through dimensionality reduction techniques like Linear Discriminant Analysis, PCA, BFO, among others. Then the processed deep features have been classified through machine learning-based algorithms like Support Vector Classifier (SVC), Random Forest, and k-Nearest Neighbor. Amongst different frameworks, MobileNetV2+LDA+SVC has produced a higher accuracy of 97.93%. From this, it is evident that when the lightweight architecture is paired up with a good classifier, one can obtain high accuracy even in computational efficiency. It can be argued that the hybrid framework is more advantageous than the end-to-end deep learning framework because it is efficient in terms of computational costs and inference time. In spite of these findings, some restrictions need to be addressed. The methodology employs the multi-phase pipeline, which complicates the entire system and requires appropriate calibration of all the components. The effectiveness of this method also depends on the quality of feature selection techniques, which might not be able to capture all the possible features from the medical image. Moreover, this research does not consider a massive dataset that could have improved the generalization ability of the proposed model. Moreover, the exclusion of interpretability of AI models is a significant drawback compared to modern AI models.

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10. Deep Learning Based Brain Stroke Detection Using Improved VGGNet

Srisabarimani and Arthi [10] introduced an enhanced VGGNet-based brain stroke detection method where architectural improvements such as addition of batch normalization layers and fine-tuning of the dropout regularization have been made to avoid overfitting. The new model has been tested against other machine learning classifiers like K-Nearest Neighbor and Random Forest, along with state-of-the-art DL models such as ResNet, SqueezeNet, AlexNet, and GoogLeNet. The new VGGNet performed best in detecting stroke and delivered an accuracy of 96.86% outperforming other models. This paper has also stressed on the importance of data pre-processing techniques which included skull stripping and contrast normalization and proved to be effective in improving classification accuracy. The comprehensive benchmarking between the various models provides useful insights into the benefits of different architectural designs for stroke classification tasks. However, the usefulness of data pre-processing techniques as highlighted in the paper is important as skull stripping has been found to help in eliminating background noise interference. Limitations include the binary nature of classification and use of MRI images with some CT scans in comparative studies.

11. Systematic Integration of Attention Modules into CNNs for Accurate and Generalizable Medical Image Classification

An ablation study [11] performed a comprehensive analysis of the inclusion of attention mechanisms such as Squeeze-and-Excitation (SE) blocks and Convolutional Block Attention Module (CBAM) within five popular CNN architectures, namely VGG16, ResNet18, InceptionV3, DenseNet121, and EfficientNetB5. This study included performance testing within two heterogenous medical imaging procedures involving brain tumor MRI and other pathology. The results showed that EfficientNetB5 with CBAM provided the best generalization ability and highest accuracy rate, which proves the significant advantage of hybrid attention modules compared to monolithic attention mechanism tuning. Channel attention mechanisms turned out to be more effective for detecting pathologies rich in textures while spatial attention was more useful for lesion localization procedures. It should be noted that the experimental set of the study provides us with generalizable insights into the application of the studied model to CT scans of strokes, considering both aspects of the disease detection. However, the only limitation associated with the research is the lack of experiments related to CT scanning.

12. Artificial Intelligence with Feature Fusion Empowered Enhanced Brain Stroke Detection and Classification for Disabled Persons Using Biomedical Images

The above mentioned study in Scientific Reports [12] presented an accessible framework for feature fusion in multi-class brain stroke classification using multiple deep learning backbone models.The paper used feature representations from CNN backbones including DenseNet and EfficientNet. These backbones undergo feature fusion in a fusion layer in order to complement one another in terms of feature representation. The feature fusion model performed better than other techniques on the Kaggle brain stroke CT dataset and demonstrates that combining the feature representations of different architectural models can result in a more comprehensive representation compared to individual feature representations of a specific model. Explainability components were also introduced in order to provide visualizations of decision boundaries. In contrast to ensembling in the prediction level, the feature fusion is a form of ensembling that performs fusion in the representation level, thereby possibly extracting more stroke-discriminative features. Societal aspect in the form of accessibility in disability healthcare context was considered in the paper. On the other hand, computational burden and higher complexity associated with performing fusion from multiple backbone models are among the limitations in the study. Comparison of this technique with attention-based single-models like CBAM-ResNet is also missing.

III. IDENTIFIED RESEARCH GAPS

Based on these reviews of 12 studies presented above are several critical research gaps are identified within the domain of deep learning-based brain stroke CT classification. These gaps span architectural, methodological, and clinical translation dimensions.

1. Limited Multi-Class Subtype Differentiation

Problem Statement: There are a considerable number of works that consider a simplified problem formulation in terms of binary classification (stroke or no stroke). The method leads to an increase in classification accuracy; however, its clinical applicability is questionable since, depending on the type of the stroke being considered (ischemic, hemorrhagic), there will be different treatment approaches. Not too many works consider multi-class classification; even fewer use a more realistic approach and apply a bigger or centre-independent dataset.

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How This Problem May Be Solved: More research needs to be done towards multi-class classification based on larger datasets collected from multiple centres. The use of transfer learning, balanced losses, better data labelling schemes, etc. could improve classification.

2. Insufficient Volumetric Analysis

Research Gap: Most of the surveyed approaches focus on classifying individual 2D CT slices. Without considering the whole volume of the scan, which plays a critical role in clinical practice when analyzing lesions, edemas, and mass effects, slice-level classification might lead to inaccurate results since some slices do not have diagnostically significant pathological structures.

How It Can Be Addressed: There are 3D CNNs, volumetric attention mechanisms within ViT architectures, and other ways to consider interdependencies between slices. For instance, curriculum learning techniques could help train the model on the most informative slices selected by a radiologist and achieve high volumetric diagnosis performance without substantial computational costs.

3. Lack of Explainability and Clinical Trust

Research Gap: Even though a lot of research utilizes Explainable Artificial Intelligence methods such as Grad-CAM or LIME, they have not been evaluated by physicians. This leads to inaccurate explanations since the highlighted portions may not correspond to the pathological region.

Gap Can Be Filled: There is an opportunity for future research to collaborate with radiologists and evaluate explanation maps. Evaluation metrics need to be developed to compare the generated explanations and annotations.

4. Class Imbalance and Data Scarcity

Research Gap: Medical datasets often suffer from imbalance, where normal cases are much more common than stroke cases, and certain stroke types are underrepresented. Traditional augmentation methods may not fully solve this issue.

Gap Can Be Filled: Advanced techniques such as synthetic data generation, semi-supervised learning, and self-supervised learning can be used to improve representation of minority classes and make better use of limited labelled data.

5. Computational Efficiency and Edge Deployment

Research Gap: Sophisticated models, such as transformer-based algorithms and ensemble models, deliver excellent performance at the cost of substantial computational requirements. As a result, it becomes challenging to deploy them in a real-time setting in hospitals, particularly in rural or underfunded regions.

How the Gap Can Be Filled: Methods that reduce the computational requirements, such as pruning, quantization, or knowledge distillation, can be applied to build efficient models for practical use cases.

6. Generalization Across Imaging Protocols

Research Gap: CT scans may differ between hospitals due to various reasons, including scanner types, image resolutions, or scanning parameters. Therefore, training on one dataset would not produce a generalizable model.

How the Gap Can Be Filled: Techniques such as domain adaptation, federated learning, or standardizing pre-processing steps could be considered.

IV. CONCLUSION

The survey provided an extensive overview of the recent deep learning methodologies employed for brain stroke classification in CT images. The reviewed studies reveal a certain development trend from CNN-based models to more sophisticated ones such as hybrid, attention-based, and transformer architectures. Moreover, there is a substantial number of highly accurate approaches which proves the ability of deep learning to aid radiologists in their diagnostics. On the other hand, there are still some issues left to be addressed by researchers such as lack of multi-class classification, insufficient evaluation of explainable models, imbalanced datasets, computational expenses, and poor generalizability.

Future research should involve the improvement of dataset size and diversity as well as better integration of medical knowledge and multimodal data in models. Apart from that, further work needs to be done concerning the interpretability issue and generalizability to different medical settings. In conclusion, the current efforts made in this field need to be transformed into practical achievements which means validation of algorithms in a medical setting.

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