The Advancements of Convolutional Neural Networks on Cerebral Hemorrhage Detection

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Abstract: Cerebral hemorrhage is a common and serious disorder that poses a serious threat to the health of the patient. Due to the shortcomings, such as the low efficiency of traditional cerebral hemorrhage detection, it is rather necessary to consider techniques combined with artificial intelligence to enhance the quality and speed of detection because of the intractability of the disease. In this paper, a method using convolutional neural networks (CNN) is considered, studied, and further discussed. Currently, deep-learning-based automated cerebral hemorrhage detection methods have gained widespread attention. These approaches have achieved rapid and accurate brain bleeding detection by analyzing head imaging data, such as computerized tomography (CT) images. Some professors adopted a special technique or structure, for example, the attention mechanism or hybrid CNN, to detect and classify the CT images, which has already gained wonderful achievements. The use of attention mechanisms or mixed CNN for brain hemorrhage testing contributes to improving the accuracy, adaptability, and efficiency of testing, which is one of the important directions of current research. However, in practical applications, some models have been poorly performed in dealing with specific types of brain bleed and have limited generalization capabilities. The focus in this field includes improving character representation, optimizing model structures, and solving data deviations to improve the generalizing capability and accuracy of models. In conclusion, this paper provides a good overview of cerebral hemorrhage detection.

1 INTRODUCTION

Cerebral hemorrhage refers to when cerebrovascular rupture or vascular wall problems occur and blood flows into brain tissue, causing increased stress and causing brain tissues to be damaged or even killed. The symptoms of cerebral bleeding may include severe headaches, nausea, vomiting, awareness loss, drainage, and body impotence (Peng, 2019; Kumar, 2023). Cerebral hemorrhage was one kind of disease that seriously jeopardized the health of human beings.

Traditional brain bleeding is usually diagnosed using the following methods: the clinic will first consider the possibility of cerebral bleeding with the patient's past medical history and clinical symptoms, and then with a Computerized Tomography (CT) of the scrotum to make a clear diagnosis (Al'Aref, 2019; Bloom, 1996). It can be observed that the traditional detection method has certain drawbacks. For example, due to the need for a doctor's judgment and CT detection, the detection time is long, and the rate is low, and in addition, misdiagnosis is easy to occur. Besides, the labor cost of the whole detection procedure is high. Therefore, it is necessary to combine the traditional detection technique with Artificial Intelligence (AI). Initially, AI can process large amounts of medical image data and perform analysis and diagnosis in a short time (Qiu, 2022). In addition, through deep learning and pattern recognition technology, AI can be trained to learn from a large amount of image data, and then AI can extract key features from it, thus making accurate prediction (Sun, 2020; Zhou, 2023). Therefore, the accuracy of AI can help reduce the risk of misdiagnosis and missed diagnosis and improve the diagnostic accuracy of cerebral hemorrhage (Wang, 2013).

In recent years, there have been many significant advances in the field of artificial intelligence, especially for deep learning algorithms. Deep

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learning (DL), for example, which uses neural networks to simulate the structure and function of the human brain for learning and pattern recognition of large-scale data, has achieved great success in image recognition, speech recognition, natural language processing, and other fields such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). With the rapid development of AI, it has been used in various fields such as engineering (Pham, 1999), education (Beck, 1996), agriculture (Eli-Chukwu, 2019) etc. It is worth noting that AI technology is also playing an important role in medical fields such as gastroenterology (Yang, 2019), radiology (Teramoto, 2019), and cardiology (Johnson, 2018). AI is usually used in medical image processing (Wang, 2013; Castiglioni, 2021), data storage, targeted therapy (Haleem, 2019) etc. For instance, AI can help detect and diagnose pneumonia because CNNs have the ability to classify medical images (Li, 2023; Račić, 2021). Although there are relatively few studies on the combination of cerebral hemorrhage and AI compared to other fields, there are still some achievements proposed. Lee et al. developed a novel deep-learning algorithm for artificial neural networks (ANN) to evaluate its feasibility for detecting Intracranial Hemorrhage (ICH) and classifying its subtypes (Lee, 2020). Zhang et al. segmented the brain parenchyma area using the Mask Region-based Convolutional Neural Network (Mask R-CNN network). Then they located the blood clot area using the threshold segmentation approach. Finally, cross-sectional contour interpolation was used to construct a 3D visualization technique for cerebral bleeding (Zhang, 2021). Due to the importance of this area, deep learning, especially CNN, has made significant breakthroughs in brain hemorrhage in recent years, it is therefore necessary to make a comprehensive overview of it.

2 METHOD

In the biomedical field, machine learning has had a significant impact on the prediction and detection of cerebral hemorrhage. Machine learning can help facilitate the identification and prediction of diseases of concern in the medical industry, and perhaps even the fairness of decision-making (Bharath Kumar Chowdary, 2022).

2.1 Framework of CNN-Based Hemorrhage Detection

Figure 1 presents the concrete process of CNN-based hemorrhage detection, which typically include the following steps: data collection, data preprocessing, model building, model training, testing and assessment, and deployment.

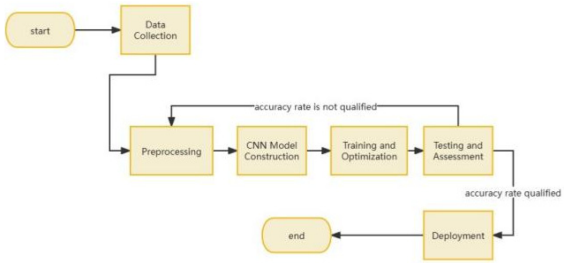

Figure 1: The structure (Picture credit: Original).

Data Collection: A large number of medical imaging data sets, such as CT scans or Magnetic Resonance Imaging (MRI) images, should be collected from hospitals or medical institutes.

Data Pre-Processing: This may include adjusting the size of the image, usually scaling it to a uniform size. Data pre-processing improves data quality and reduces noise interference through operations such as cleaning, converting, and naturalizing raw data, thereby helping machine learning models to learn and generalize better. For example, localization improves the stability of model training, increases the convergence rate, and effectively solves the problem of gradient disappearance or explosion. Data enhancement can scale up data sets, improve the generalization capacity of models, etc. Through these data preprocessing techniques, models can be trained, generalized, and robust, thereby better addressing actual problems and improving the performance of machine learning models.

Model Construction: CNN is a deep neural network consisting of the convolutional layer, the pooling layer, and the fully connected layer. The convolutional layer is used to extract the characteristics of an image and generate a series of characteristics by rolling the convolution kernel onto the image. The pooling layer is used to reduce the dimensions of a feature map, reduce the number of calculations, and retain the important characteristics. The Fully Connected Layer maps the features obtained by the Pooling Layer and connects the Output Layer for the final classification or regression task.

Training and Assessment: The next step is to train the built-in CNN model using the ready-made data set. It is also important to use a separate test set to evaluate trained CNN models, with indicators such as accuracy, recall rate, precision, and F1 scores assessing the performance of models.

Deployment: once the model has been evaluated and reached the required performance indicators, it can be deployed into practical applications.

2.2 CNN Combined with Attention Mechanisms

Attention mechanisms are used in neural networks to focus on specific parts of the input sequence or image, enabling models to attach greater importance to relevant information.

Alis, D. et al. employed a unique DL architecture, a hybrid CNN recurrent neural network (RNN) with an attention mechanism, to detect and subcategorize ICH on non-contrast head CT images (Alis, 2022).

Initially, continuous, uncontrolled enhanced CT scans of the head are obtained from the emergency departments of five tri-methyl clinics. Then Five neuroscientists evaluate the images collected to determine the presence of bleeding and, if any, mark their subtypes (intraparenchymal hemorrhage (IPH), intraventricular hemorrhage (IVH), subdural hematoma (SDH), epidural hematoma (EDH), and subarachnoid hemorrhage (SAH)). Using the TensorFlow deep learning library, a joint CNN-RNN model is constructed on a customized workstation. The model uses InceptionResNetV2 as the basic network to extract the most relevant features of the image. The extracted images are delivered to a two-way RNN with a focus layer to deliver information between images. The attention mechanism helps to concentrate the most pertinent data needed by the two-wheel RNN to focus on the task. It uses three different window-point settings to emphasize contrast differences between background and ICH and performs some conventional image pre-processing operations before delivering the image to the network. After that, these professors divide the data set into training sets and validation sets, with four centers of data used for the training model and one center for the validation model. Besides, an improved NormGrad method has been used to generate a Gradient-weighted Class Activation Mapping (Grad-CAM) to highlight the decision-based basis of the model on a given task.

A. Hussain et al. propose a novel deep learning-based CNN model to efficiently detect and classify brain hemorrhage and its subtypes. This paper describes a hybrid attention-based ResNet architecture for ICH detection and classification (Hussain, 2022).

The study used 434,166 CT scan samples from the RNSA-2019 dataset, including five separate ICH categories. Then researchers preprocess these CT images. They used the Deep Volume Generation Confrontation Network (DCGAN) to generate CT scan images of the epidural hemorrhage (EH) category to address data set category imbalances. In addition, feature extraction is done using the attention-based ResNet-152V2 architecture. Feature selection, redundancy removal, and de-dimensionation operations are performed using master component analysis. Besides, they used the gradient enhancement algorithm XGBoost. The next step is to optimize the model's learning process by performing super parametric adjustments manually to improve its performance. After optimizing the model, experiments with Python programming languages in Kaggle Jupyter Notebook were carried out to create deep learning models and evaluate their performance. Finally, some indicators, including accuracy, precision, recall rate, F1 score, true rate, true negative, AUC, etc., were used to evaluate the performance of the model.

2.3 Hybrid CNN

Hybrid CNN hemorrhage detection methods enhance the accuracy, robustness, and generalization of intracranial bleeding detection by combining different types of CNN models.

For example, Iqbal et al. use hybrid machine learning algorithm to detect brain hemorrhage.

The study used a CT brain imaging data set from Kaggle as input. Then the study selected different 3D volume neural network (3D VNN) models, including Visual Geometry Group-16 (VGG-16), Visual Geometry Group-19 (VGG-19), etc., as well as other models such as the Multilayer Perceptron Model (MLP), Support Vector Machine (SVM), and Random Forest (RF). Besides, hybrid machine learning algorithms are designed by combining different 3D VNN models (such as VGG-16 and VGG-19) with Random Forest and Multilayer Perceptron (MLP) classifiers. It uses the selected model to train CT brain images and test the accuracy of the model. Based on the results, the authors claimed that the combined method of the VGG-16 and MLP classifiers achieved an optimal accuracy of about 97.24%. The study also uses explanatory AI technology to explain the model's predictions for the brain hemorrhage category, making the predictive process of the model more understandable (Iqbal, 2022).

3 DISCUSSION

By analyzing current research, CNN can indeed improve the efficiency of the detection process. However, there are some limitations and challenges in current studies that influence the promotion of this method.

Initially, for example, there may be imbalances in brain and non-brain bleeding samples, resulting in poor performance of models in a few categories. Moreover, medical imaging data may be influenced by realistic factors, so the data needs to be cleaned up and preprocessed.

Secondly, it is necessary to consider the interpretability and domain knowledge of models to better serve doctors and patterns. Despite the use of interpretable AI technologies to interpret predictions, the interpretability of models remains a challenge for the medical field (Iqbal, 2022). The complexity of some deep learning models may limit their interpretability, which requires weighing the relationship between model performance and interpretability. Besides, as for the domain knowledge, the need for brain hemorrhage testing in different clinical scenarios may vary, so targeted models and solutions are needed, which is also a deficiency of current research.

Thirdly, model generalization is also a very important factor. Model-trained datasets may differ from actual clinical data and require consideration of how to enhance the model's generalization capabilities across different data sets. Inadequate generalization may be due to the limitations of the training data set, such as the lack of diversity of data and the inability to cover various types of cerebral bleeding. In addition, in terms of characteristic representation, the various manifestations of brain bleeding may not be captured. These factors can result in the poor performance of the model for different types of cerebral hemorrhage.

But in the future, through some methods and research, these issues may be improved continuously. Here are some possible solutions.

Firstly, it is possible to combine Shapley Additive Explanations (SHAP), a method for explaining model predictions that can help to understand the degree of the model's contribution to the input characteristics, values, and visualization techniques, such as generating thermal charts or local significance charts, to visually present the model's critical characteristics and diagnostic basis for brain hemorrhage detection, enhancing the interpretability and credibility of the model.

Secondly, transfer learning can be used. Using transfer learning methods such as feature extraction and model fine-tuning, existing brain hemorrhage detection models are applied to new datasets and adjusted accordingly to the characteristics of the new data sets to improve the performance of the model in the new dataset (Qiu, 2019).

Thirdly, the use of field-specific techniques, such as field counter-training and field-to-field distance measurement, enables the model to fully adapt to the data characteristics of different medical institutions and improves its generalization capacity, which is also a possible solution.

Furthermore, different options might be examined from other perspectives on expert systems and federal learning. Developing an expert system with medical specialists to codify expert information using knowledge graphs, rules engines, and other technologies, as well as to deliver more complete, accurate brain hemorrhage testing and diagnosis support using machine learning models, Creating a federal learning framework, utilizing technologies such as secure multifaceted computing, differential privacy, sharing and updating model parameters across several medical institutions, and enhancing the performance and applicability of brain hemorrhage testing models.

4 CONCLUSIONS

As the research has demonstrated, investigations have indicated that CNN has produced exceptional results in cerebral hemorrhage diagnosis, displaying excellent accuracy and sensitivity in the field of medical imaging analysis. CNN technology can assist clinicians in enhancing the efficiency and correctness of their diagnoses in automated cerebral hemorrhage detection. As a result, it can play an important role in clinical sectors such as supporting doctors in rapidly and properly diagnosing illnesses, initiating early treatment, and lowering patient death and disability rates. However, there are still constraints that need to be investigated further, such as the poor quality of the data, the model interpretability, domain knowledge, and model generalization. It only covers the CNN algorithm for detecting brain hemorrhages, which has certain drawbacks. Indeed, other types of algorithms should be investigated in the future. As a result, CNN technology must be constantly enhanced in order to be suitable for wider clinical use and diffusion in the future.

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