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Brain Tumor Detection Using Convolutional Neural Network

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ABSTRACT

Magnetic resonance imaging (MRI) serves as a pivotal tool in detecting brain tumors, a critical aspect of medical diagnosis. Early identification of these tumors is paramount in assessing their potential malignancy. Leveraging deep learning, a powerful computational technique for image analysis, has emerged as an effective approach in this realm. Its versatility lies in its ability to classify images without relying solely on domain expertise, but rather on the availability and diversity of data. Among deep learning architectures, Convolutional Neural Networks (CNNs) stand out for their efficacy in image classification tasks. This study undertakes a comparative analysis of two CNN models to determine the optimal one for classifying brain tumors in MRI images. Through rigorous experimentation, we achieved a prediction accuracy of up to 90%, underscoring the potential of CNNs in medical imaging applications.

Introduction

In 2018, Indonesia stood as the 8th country with the highest number of cancer patients in Southeast Asia, ranking 23rd across Asia according to the Indonesian Ministry of Health. Among cancers, brain tumors emerge as the second leading cause of mortality following breast cancer, with a higher prevalence among women. Over the past decade, the incidence of brain tumors has shown a consistent rise in various nations. Detecting these tumors early is crucial for effective intervention and preventing more aggressive diseases.

Medical imaging plays a pivotal role in diagnosing brain tumors, with MRI being a favored technique due to its non-ionizing radiation nature. Researchers heavily rely on MRI for its effectiveness in detecting these tumors.

Numerous studies have been conducted on brain tumor detection methodologies. Parveen et al. employed a combination of Fuzzy C-Means and SVM techniques. Their approach utilized Fuzzy C-Means for brain segmentation and subsequent feature extraction using Gray Level Run-Length Matrix (GLRLM), achieving an accuracy of 83.33% with SVM classification.

Avizenna et al. proposed a method using fluid-attenuated inversion recovery (FLAIR) for classifying MRI images into normal and abnormal brains. Their study utilized the BRATS 2017 database, employing multinomial logistic regression models with ridge estimators for classification, achieving results assessed through sensitivity, specificity, and accuracy with cross-fold validation.

However, unsupervised segmentation methods pose challenges, requiring human intervention and facing obstacles like varying brain shapes and locations among patients. Additionally, discrepancies in scanned images due to differences in scanning devices further complicate analysis.

To address these complexities, this paper proposes employing CNN, which excels in feature extraction while preserving spatial information. CNNs, tailored for processing two-dimensional data, offer advantages in simplicity and effectiveness, albeit demanding significant data and time for training. This study presents two CNN models for comparative analysis to determine the optimal model for brain tumor classification.

Literature Review

2.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of deep learning models primarily used for image analysis. They excel at tasks like image recognition, object detection, and segmentation. CNNs feature layers that learn to extract hierarchical features from input images through convolutional filters. They are trained on large datasets using backpropagation to minimize prediction errors. CNNs have revolutionized various fields, including computer vision, medical imaging, and natural language processing, by automating feature extraction and achieving state-of-the-art performance. Despite their effectiveness, challenges remain, such as the need for large labeled datasets and model interpretability. Ongoing research aims to improve CNN efficiency, generalization, and applicability in emerging domains like robotics and personalized medicine.

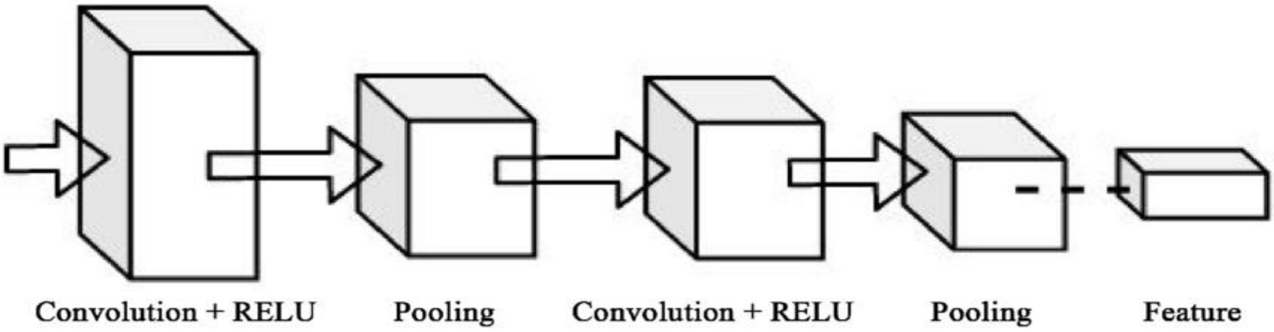

Figure 1. Convolutional Neural Networks

2.1.1 Convolution Layer

Convolutional layers are fundamental components of Convolutional Neural Networks (CNNs), designed to extract features from input data, particularly images. They consist of filters or kernels that slide across the input image, performing convolution operations to produce feature maps. Each filter learns to detect specific patterns or features, such as edges or textures, through the convolution process. Convolutional layers are characterized by parameter sharing, where the same set of filter weights is applied across different spatial locations in the input, enabling the network to efficiently learn and detect features regardless of their position. These layers play a crucial role in capturing spatial hierarchies of features in images, facilitating tasks like image recognition, object detection, and segmentation.

2.1.2 Subsampling Layer

Subsampling layers, also known as pooling layers, are essential components of Convolutional Neural Networks (CNNs) used to reduce the dimensionality of feature maps. They operate by downsampling the input data, typically through operations like max pooling or average pooling, which extract the most important features while discarding redundant information. By reducing the spatial resolution of the feature maps, subsampling layers help control overfitting, improve computational efficiency, and enhance the network's ability to generalize to unseen data. Subsampling layers play a crucial role in CNN architectures by providing translation invariance and spatial hierarchy, making them particularly effective in tasks like image classification and object recognition.

2.1.3 Fully Connected Layer

Fully connected layers, also called dense layers, are crucial components of Convolutional Neural Networks (CNNs) responsible for making predictions based on the extracted features. Each neuron in a fully connected layer is connected to every neuron in the preceding layer, forming a dense network of connections. These layers perform classification or regression tasks by learning complex relationships between the extracted features and the target labels. Fully connected layers are typically located at the end of the CNN architecture and are trained using techniques like backpropagation and gradient descent to minimize prediction errors. They play a vital role in CNNs for tasks such as image classification, object detection, and semantic segmentation.

3.Method

3.1 Dataset

In brain tumor detection with CNNs, we start with a dataset of MRI images annotated by experts to indicate tumor presence or absence. These images undergo preprocessing like resizing and normalization. We split the dataset into training, validation, and testing sets. Training data is used to train the CNN, adjusting its parameters to minimize errors. Validation data helps fine-tune the model, while testing data evaluates its performance. We ensure a balanced distribution of tumor and non-tumor cases across subsets. This dataset is crucial for training, validating, and assessing the CNN's effectiveness in detecting brain tumors.

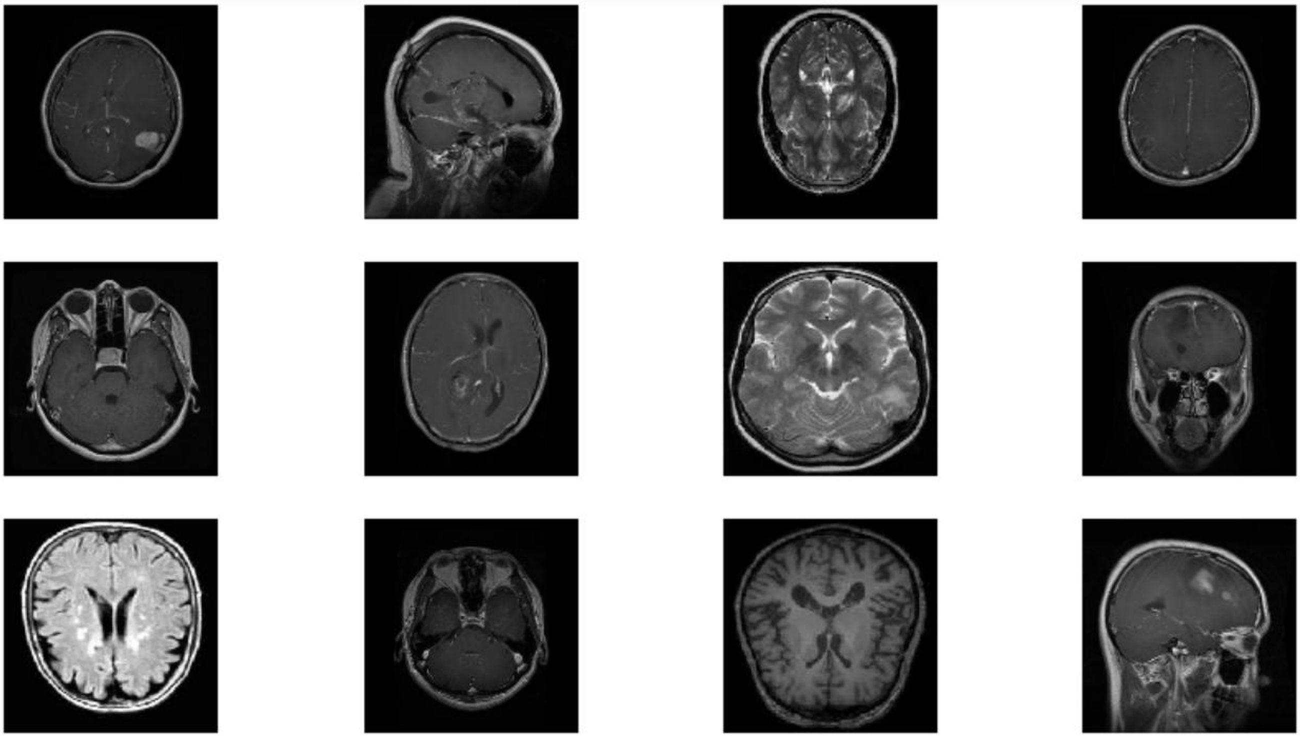

Figure 2. Dataset

3.2 Data Augmentation

Due to insufficient data for training CNNs, augmentation methods are employed to address the imbalance. Augmentation algorithms leverage statistical information to generate diverse image variants. This enhances CNN segmentation accuracy. In this study, each tumor image is segmented into 6 variations, while non-tumor images yield 9 variations. After augmentation, the dataset comprises 1085 tumor-containing (53%) and 980 tumor-free samples (47%), totaling 2065 images.

3.3 Image Pre-processing

Pre-processing plays a critical role in ensuring smooth training by addressing variations in intensity, contrast, and size among images. The initial step involves wrapping and cropping the input image. During wrapping, the image is examined to identify the main object's edges. The maximum edge is determined to preserve the object's integrity during cropping. Subsequently, the image is resized to a standard shape, typically (265, 265, 3), to accommodate variations in image sizes within the dataset.

Normalization is then applied to scale pixel values to a range between 0 and 1. This normalization step aids in standardizing pixel intensities across images, facilitating the learning process of the CNN model. Overall, these pre-processing techniques ensure uniformity and enhance the compatibility of images for effective training in brain tumor detection using CNNs

3.4 Model CNN

A CNN, or Convolutional Neural Network, stands as a pinnacle in deep learning for processing and deciphering visual data, notably images. Comprising layers such as convolutional layers, pooling layers, and fully connected layers, CNNs excel in extracting intricate features like edges and textures from input images. By reducing spatial dimensions through pooling layers and leveraging fully connected layers for classification, CNNs have redefined tasks like image classification, object detection, and segmentation. Their versatility extends across diverse domains, from computer vision to medical imaging and natural language processing. CNNs' ability to learn hierarchical representations directly from raw data underscores their significance as potent tools in decoding complex visual information.

4.Result and Discussion

The experiments detailed in this article utilized a dataset comprising 2065 images, with 1085 samples containing tumors and 980 samples devoid of tumors. The dataset was split into three subsets: 70% for training, 15% for validation, and 15% for testing. Each experiment was repeated 10 times using the previously constructed CNN model, with 25 epochs and 32 batches per run.

The results were analyzed by comparing standard deviations, mean values, and mean losses, accuracies, and F1 scores. Tables 3 and 4 present the experiment outcomes. In the initial CNN model employing one convolutional layer, the average training accuracy was 94%, with a loss of 0.14181. However, there was a notable discrepancy with the test data, yielding an average accuracy of 85% and a loss of 0.44037. In contrast, the second CNN model, featuring two convolutional layers, demonstrated improved performance. It achieved a training accuracy of 96% with a loss of 0.10046, and a test accuracy of 93% with a loss of 0.23264. Additionally, the F1 score for the second model reached 92%, albeit with a longer training duration compared to the first model

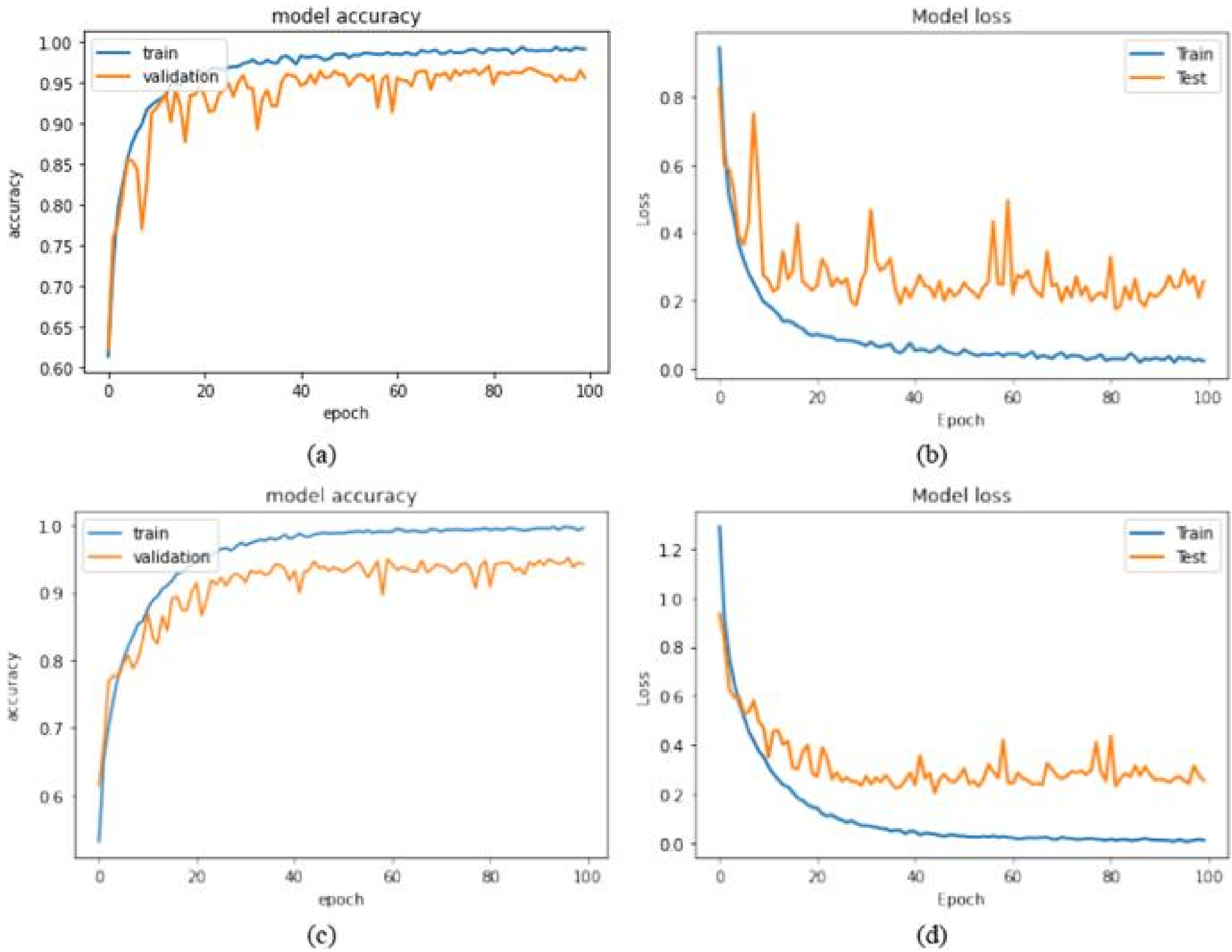

Figure 3. Result

Conclusion

Convolutional Neural Networks have demonstrated effectiveness in diagnosing brain tumors from MRI images. This study achieved an accuracy rate of 93% and a loss value of 0.23264. The depth of the CNN architecture impacts classification quality; increasing the number of convolutional layers enhances accuracy, albeit at the expense of longer training times. Employing image augmentation techniques can enhance dataset diversity, leading to improved classification outcomes. Moving forward, augmenting the dataset with additional images could further refine classification accuracy. Additionally, future research could explore specialized tumor classification to enhance diagnostic precision.

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