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The investigation of application related to deep learning on brain tumor diagnosis

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Abstract. Brain tumor has been a serious disease to human beings for a long time. Brain tumors have posed a significant health threat to humanity for many years. If left untreated in its early stages, a brain tumor can become malignant, drastically reducing survival chances. Throughout the decades, numerous individuals have endured the hardships of brain tumors, and tragically, some have succumbed to this condition. However, deep learning techniques offer a promising avenue for precise and efficient brain tumor diagnosis. Utilizing this technology enables the early detection and treatment of benign tumors, potentially saving lives and preventing unnecessary loss. In this review paper, two previous research on how different deep learning models perform on the brain tumor diagnosis would be illustrated. In the first research, the performance of five models would be compared with each other. In the second research, Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) would be compared with each other. Furthermore, the examination of two research methods will delve into how various techniques can enhance model performance. Deep learning techniques also find numerous real-life applications. The two important applications are Home Diagnosis and In-Hospital Assistance, and the benefits of applying deep learning techniques in these two areas would also be illustrated. In addition, several suggestions would be proposed based on the applications of deep learning technique.

Keywords: Brain Tumor, Deep Learning, Machine Learning.

1. Introduction

The emergence of a brain tumor is marked by the anomalous proliferation of cells within the cerebral region. Individuals who get brain tumors would usually suffer from headaches, seizures, nausea, memory problems, and fatigue as well as even lose their lives. The brain tumor has been posing serious threats to the health of the human society over the past decades. The statistics has demonstrated that around 24, 810 adults in the United States were confirmed cases with cancerous brain tumors. Additionally, it is estimated that 18, 990 deaths from cancerous brain tumors occurred in the United States in 2023 [1]. Nevertheless, the brain tumor is unquestionably curable. There are 4 stages in total for brain tumors. At stage 1 and stage 2, the brain tumor is non-cancerous and tends to grow slowly. However, at stage 3 and stage 4, the brain tumor would become cancerous and would rapidly spread to tissues around it. As a result, if people could detect brain tumors and treat them in stage 1 and stage 2, the patients would likely get recovered from them. Therefore, it is imperative to figure out methods to efficiently detect brain tumors to treat them in the stage 1 and stage 2. In this case, machine learning approaches can be considered for detecting brain tumors early due to their excellent prediction ability.

One popular machine learning technique used in detecting brain tumors is the deep learning technique.

There are various approaches used in the deep learning technique for brain-related analysis [2-7]. For instance, Nadim Mahmud Dip et al compared two deep learning approaches by using the object detection framework You Only Look Once (YOLO) and the deep learning library FastAi [5]. Specifically, YOLOv5 was employed as a model in YOLO framework, and the object classification model was built using the cnn_learner class in the FastAi library. The research was implemented on a subset of the BRATS 2018 dataset that had 1992 Brain Magnetic Resonance Imaging (MRI) scans. The result showed that the FastAi model has a higher accuracy than YOLOv5 model [5]. Also, ZainEldin et al proposed a deep learning model called Brain Tumor Classification Model based on Convolutional Neural Network (BCM-CNN). It would achieve an optimization of CNN hyperparameters by utilizing an algorithm called Adaptive Dynamic Sine-Cosine Fitness Grey Wolf Optimizer (ADSCFGWO). Additionally, there was a training model built with Inception-ResnetV2. This training model employed Inception-ResnetV2, the pre-trained model, to improve the brain tumor diagnosis. This model had binary outputs 0 and 1, where 0 meant there is no brain tumor, and 1 meant there exists a brain tumor. The results demonstrated that the BCM-CNN model has a better result because of the hyperparameter optimization of CNN [6]. The motivation for using deep learning on brain tumor diagnosis is to increase the efficiency and accuracy of the diagnosis so that the brain tumor could be treated early.

The remainder of the paper is organized as follows. The main body part would contain the Method part and the Application and Suggestions part. In the Method part, different research methods in Deep Learning will be demonstrated. In addition, the analysis of the different methods will be performed. In the Applications and Suggestions part, different applications of Deep Learning will be demonstrated. Also, several suggestions on the future of Deep Learning will also be illustrated. Finally, the conclusion part will summarize the methods and their analysis results and the suggestions. Also, several future outlooks would also be illustrated in the conclusion part.

2. Methodology

2.1. Different models on the brain tumor diagnosis using deep learning

2.1.1. Procedure. This section will illustrate a comprehensive overview of the procedure of previous research on the performance of different models on the brain tumor diagnosis using deep learning technique.

The procedure of the research is demonstrated below.

Dataset Collection: Collecting dataset for model training, model validation, and model testing. The dataset could be collected online.

Language and tool used: Python has been used as the programming language. It is a high-level language with a user-friendly interface. Furthermore, it’s worth noting that this language is both free and open-source, offering users access to a wealth of libraries. Moreover, the tool utilized for Python code development was Google Colab, chosen primarily for its exceptional speed performance thanks to its utilization of fast GPU resources.

Data Preprocessing: Since the Brain MRI images in the dataset have various size, the priority would be to adjust the image sizes. Specifically, the image sizes were all adjusted to 200 by 200 pixels. In addition, all the images were normalized to the ImageNet standard.

Afterwards, the image collection was classified into two forms, uploaded to a Google Drive account. To verify if the upload is done correctly, Python would be used in the Colab environment.

Augmenting Data: Although having a dataset with a great number of data is essential for the deep learning model to achieve a good performance, augmenting images that were already collected could be used to improve the model performance without obtaining additional images. Five augmentation techniques have been utilized which are Rotation, Width Shift, Height shift, horizontal flip, and vertical

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flip. For the Rotation augmentation, the safety is dependent on the degree of rotation, which is between 1degree and 359 degrees. Also, shifting and flipping techniques are useful in summarizing more details of interested objects.

Models: There is a model created from scratch. In addition, there are four pre-trained models used in this research which are VGG16, ResNet50, MobileNet, and InceptionV3.

Models Training and Validation: The models will undergo training using the train set and validation using the validation set. Throughout the training process, we will monitor and plot metrics such as training accuracy, training loss, validation accuracy, and validation loss across different epochs. Additionally, checkpoints will be incorporated into the model to monitor validation accuracy and prevent overfitting.

Model Testing: The models will be tested using the test set. The testing accuracy will be calculated.

Evaluation Metrics: Training Accuracy, Validation Accuracy, Training Loss, Validation Loss, Testing Accuracy

2.1.2. Dataset. The dataset used in this research contains 10000 MRI images of brain. Specifically, 5000 images have brain tumor and 5000 images do not have brain tumor. In addition, the format of the images in the dataset was JPG in order to fit well with the models.

2.1.3. Models. The details of the model used in this research are shown in this section.

Model created from scratch: The custom-built model comprises 12 convolutional layers and a fully connected hidden layer. The output layer employs softmax activation to generate probabilities for each class. Additionally, the network was optimized using the Adam optimization technique.

When the model is trained, batches will be iterated by the model. For every batch, gradients will be calculated, and the updates will be made to the network weights. Training will run until the convergence of the loss.

VGG16 model: It has 16 convolutional layers and a hidden layer that is connected fully. The model has

dropout layers which prevent overfitting. Also, ReLU activations exists in all layers but not in the output layer.

ResNet50 model: It has 50 convolutional layers and a hidden layer that is connected fully [7]. The model has dropout layers which prevents overfitting. Also, ReLU activations exists in all layers but not in the output layer.

MobileNet model: It has 28 convolutional layers and a hidden layer that is connected fully [8]. The model has dropout layers which prevents overfitting. Also, ReLU activations exists in all layers but not in the output layer.

InceptionV3 model: The pre-trained model InceptionV3 network has 28 convolutional layers and a hidden layer that is connected fully. The model has dropout layers which prevents the overfitting. Also, ReLU activations exists in all layers but not in the output layer [9].

2.2. CNN and ANN on brain tumor diagnosis using deep learning

2.2.1. Procedure. This section will illustrate a comprehensive overview of the procedure of previous research on the comparison of the performance of CNN and ANN on the brain tumor diagnosis using deep learning technique. The procedure of the research is demonstrated below.

Dataset Collection: Collect dataset containing MRI images of brain tumor for model training, model validation, and model testing. The dataset could be collected online.

Data Resizing and Normalization: The images in the dataset have different sizes. Therefore, the images have to be resized to the same size. Specifically, the images were resized to 256 by 256 pixels. In addition, all the images were normalized.

Create Models: The models used in this research are CNN and ANN.

Models Training and Validating: Models will be trained using the training set and validated using the validation set. The training accuracy, training loss, validation accuracy, and validation loss versus epochs will be plotted.

Models testing: The models will be tested using the test set, and the testing accuracy will be calculated.

Draw the Confusion matrix (CNN Only): The confusion matrix will be shown for model validation and model testing.

Evaluation Metrics: The evaluation metrics for both models are test accuracy, F1 score, and Precision.

2.2.2. Dataset. The dataset was obtained from the GitHub. It has MRI images of brain. In addition, it has two folders in which one folder contains the brain image without tumor and another one contains the brain image with tumor. The two folders have 2065 images in total, with 1085 images with tumor and 980 images without tumor. In addition, the images have different sizes.

2.2.3. Models. The details of model CNN and ANN are shown in this section.

Artificial Neural Network (ANN): There are 7 layers in the ANN. The flatten layer, also the first layer, transforms the 256 by 256 images to single dimensional array. The subsequent five layers, which are dense layers, are equipped with the ReLU activation function. The neuron counts in each of these layers are 128, 256, 512, 256, and 128, respectively, making up the hidden layers. The final layer, also a dense layer, functions as the output layer with a sigmoid activation function and a single neuron representing the two classes. The model is compiled using the Adam optimization technique and the binary CrossEntropy loss function.

Convolutional Neural Network (CNN): Through implementing different layers, the CNN model would be formed. The input images are resized to 256 by 256 Pixels. Then, the convolve layer will applied on the input image. For the convolve layers, the numbers of filters are 32, 32, 64, 128, 256. The layer that is connected fully is implemented by calling the dense method with the 256 unit and the activation function ReLU. The output layer contains only one unit to refer to the two classes and the activation function sigmoid [10].

2.3. Analysis of methods

In both experiments, several models were used to compare with each other. The training, validation, and test data were collected and compared. However, to improve the performance of the models in both experiments, one could use a larger training dataset, additional image augmentation methods [9, 10].

3. Applications and suggestions

3.1. Applications

3.1.1. Home diagnosis. Using deep learning for brain tumor diagnosis could let people test if they have brain tumor at home. By uploading the MRI image of the brain to a computer, the deep learning method could provide accurate results on the computer. This is especially convenient for elder people who prefer to stay home. In addition, this could allow people to avoid long wait time at hospitals so that people will have time to do other important work. More importantly, the high accuracy of the diagnosis using deep learning would also make the diagnosis quite safe.

3.1.2. In-Hospital assistance. The deep learning technique for brain tumor diagnosis could also be used to provide crucial assistance to the hospital. With the deep learning, the result could be available over a short period of time, which is much less than the time for the doctor to do the diagnosis. Therefore, it would greatly reduce the diagnosis time and the wait time of patients. Reducing the wait time for patients

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would likely attract more patients to hospitals, generating more profits for hospitals. In addition, due to the high accuracy of the deep learning technique, it would reduce the risk of faulty diagnosis.

3.2. Suggestions

Given that deep learning for brain tumor diagnosis can potentially be applied for in-home use, it is advisable to consider mass-producing these diagnostic devices. The initial distribution should prioritize households with elderly residents, as physical limitations may hinder their ability to visit hospitals. Furthermore, long-term care facilities should be equipped with these diagnostic devices to enhance diagnostic efficiency and accuracy. If some family still need the devices, they could purchase them for their own need. For the hospital, it is strongly advised to first equip the diagnosis device in emergency departments, as it requires quick and accurate results. Then, other departments could purchase the equipment for their own need.

4. Conclusion

In this paper, the two research on the different deep learning models performance on the brain tumor diagnosis have been illustrated. Also, to improve the performance of different models in the two research, larger training dataset, additional image augmentation could be used. Furthermore, the deep learning technique could be applied in home diagnosis and hospital assistance for brain tumor diagnosis. Home diagnosis offers time-saving benefits, particularly for elderly individuals who may face mobility challenges, and it boasts a high level of accuracy. For the hospital assistance, it would reduce the diagnosis time and increase the accuracy of testing, reducing wait time and attract more people to the hospital. As a result, more profit would be generated in the hospital. Based on the application in home diagnosis, the diagnosis device should first be allocated to houses with elder people and long-term care centers. Then, people could purchase based on their own need. For the application in hospital assistance, the diagnosis device should first be allocated to the emergency department and then other people could purchase according to their own need.

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