A Hierarchical Dual-Branch CNN with Feature Concatenation for Brain Tumor Classification

Van-Vu Ngo, Quoc-Cuong Nguyen, Chih-Min Lin

***Abstract*-- This paper presents a hierarchical dual-branch convolutional neural network (Hierarchical Dual-Branch CNN with Feature Concatenation) for brain tumor classification; this model uses a feature concatenation structure and is trained by a brain tumor MRI dataset. The model's ability to efficiently extract image features improves the accuracy of recognizing various brain tumors and also for non-tumor cases. The performance of the model is evaluated and compared with transfer learning methods based on popular architecture such as MobileNetV2, and the structure-based model proposeds in previous researches. According to experimental results, the proposed method performs better on the test dataset across a range of assessment metrics than the other models.**

***Keywords*—CNN, Transfer Learning, Brain Tumor, MobileNetV2.**

I. INTRODUCTION

Brain tumors are among the hazardous circumstances that can have substantial influence on a patient's health and even endanger their life, particularly if the tumor is large and malignant. In order to treat brain tumors promptly and lower mortality while increasing the chance of the patient surviving, early identification and precise diagnosis are essential. Consequently, identifying and diagnosing brain tumors is a crucial medical task in medicine, and medical imaging technology has become a powerful support tool in this process. Currently, brain tumor diagnosis mainly relies on doctors analyzing medical images, such as MRI or CT scans. However, this manual image interpretation is not only time-consuming but can also lead to errors, affecting the accuracy of the diagnosis results. In this context, the strong development of artificial intelligence algorithms, especially machine learning and deep learning, has great potential to support the classification and detection of brain tumors from medical images. These techniques not only save time but also reduce errors, while improving the accuracy of diagnosis, although they still face many challenges in processing and analyzing complex medical data. This topic is currently attracting great attention from researchers. The convolutional neural networks (CNNs) are widely used image processing approaches that can automatically extract features and have practical uses in medical image classification. An ensemble deep learning model using ResNet50 and EfficientNet-B7 was proposed by Singh [1] to enhance performance in categorizing brain tumors from MRI images. In [2], Hafeez designed a CNN model which includes 15 layers for classifying three different kinds brain tumors. Sakib presented a hybrid VGG model for brain tumor classification, which showed significant improvement in classification performance by incorporating additional CNN layers to enhance feature extraction [3]. In addition, the application of transfer learning models has also shown significant effectiveness in medical image analysis and is becoming more and more common [4]-[6].

Realizing the advantages of using branching models, in this paper, we built a model which contains a simple structure of five hierarchical CNN levels, in which each level is divided into two branches with the same structure, to maximize the ability to extract image features and overcome the limitations of single-stream CNN networks. The proposed model is trained by the brain tumor dataset after applying preprocessing steps. In addition, we also use this dataset to train transfer learning models from popular architecture (MobileNetV2) with the structure proposed in [2]. Afterwards, evaluate the proposed approach to the test set using F1-score, recall, accuracy, precision, and loss. The results show that our model is superior in most evaluation metrics.

II. METHODOLOGY

A. 2.1 Dataset

In this research, we used the Brain Tumor MRI Dataset published on Kaggle (at the following link: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset). The dataset is a combination of three publicly available sources: Figshare, the SARTAJ dataset, and Br35H. In total, the dataset contains human brain MRI images, divided into four classes: glioma, meningioma, no tumor and pituitary tumor. Fig. 1 illustrates these four classes.

Before training, the data is preprocessed through the following steps: resizing all images to the size of 150×150×3, and normalizing pixel values into range 0–1. After processing, the data are splitted into training set and testing set, with the specific numbers illustrated in Table 1.

The training dataset is used to train the model, where the model learns and updates its parameters based on this data. The test dataset is used to evaluate the overall performance of the model on unseen data, thereby reflecting the model's applicability in practice.

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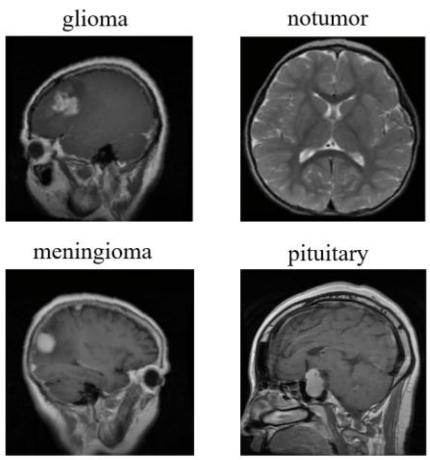

Fig. 1. The types of tumors in the Brain Tumor MRI Dataset.

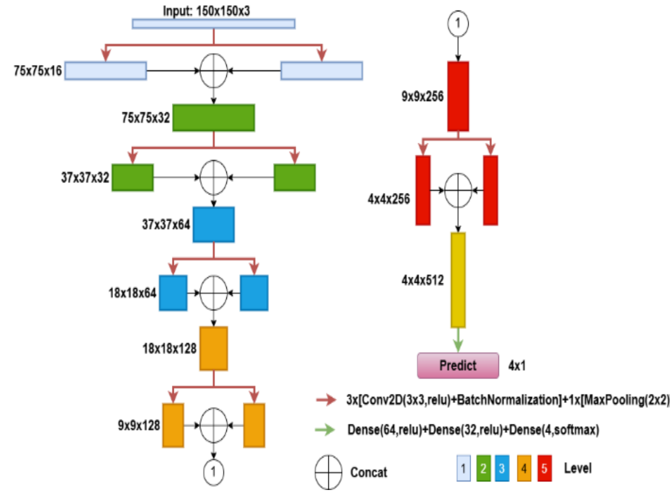

Fig. 2. Architecture of the proposed model.

Table 1. Number of samples per class in the dataset.

Class / Dataset	Glioma	Meningioma	Notumor	Pituitary
Training Set	1321	1339	1595	1457
Testing Set	159	161	237	156

III. Proposed Model

Our proposed model consists of five hierarchical CNN levels designed for extracting features from input images. Each level adopts one branched structure, as illustrated in Fig. 2. The output dimensions of each intermediate level are clearly shown in the diagram. Within each level, the input of each branch is processed through three convolutional layers (Conv2D) with the same number of filters and ReLU activation functions, followed by a Batch Normalization layer and a Max Pooling layer. The features extracted from all branches are then concatenated and passed to the next level. The output of the fifth level is subsequently fed into a series of Dense layers to perform the final classification using a softmax activation function.

The branches in each level aim to raise the model’s capacity to extract a richer set of features from the input images. By avoiding the limitations of a single-stream CNN architecture, this structure allows for more diverse and comprehensive feature representation, ultimately improving learning performance and classification accuracy.

The models are trained and evaluated respectively on the datasets following the preparation steps described above. Accuracy is the evaluation metric and categorical cross-entropy is the loss function. A starting learning rate of 0.0001 is applied when using the Adam optimizer.

If the performance is not improved after five consecutive epochs, the learning rate is set to decrease by a factor of 0.9. With a batch size of eight, the models are trained with a default number of epochs of 50 and select the best state. The proposed approach achieved the best performance at epoch 48th.

IV. Performance Metrics

The parameters such as Accuracy, Precision, Recall, and F1-score are used to assess the proposed model's performance, as presented in (1), (2), (3).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

in which TP, TN, FP, and FN represent the true positive, true negative, false positive, and false negative, respectively.

V. Simulation Result

In this section, we give the evaluation results on the test dataset using the following metrics: accuracy, loss, precision, recall, and F1-score. Additionally, the performance of our proposed method is compared with several transfer learning models based on pre-trained weights from MobileNetV2 structure on the ImageNet dataset. The output layers of these models were replaced with Dense layers to better suit our classification task. The CNN model proposed in [2] is also implemented and evaluated on this dataset. The detailed results are presented in Table 2, 3, 4. The results presented in Table 2, 3, 4 show that the proposed model outperforms the other ones. Specifically, in Table 2, the proposed model achieves the highest accuracy at 98.88%, next is CNN model [2] with the accuracy 97.76%. The transfer learning models based on MobileNetV2, achieve 95.79% and 94.39%, respectively. Additionally, the proposed model shows the lowest loss, with a value of 0.0560. In Table 3, 4 the detailed evaluation measurements like precision, recall further highlight the superiority of the proposed method. The proposed model achieves better performance on most of the evaluation parameters.

Table 2. Test accuracy and loss results.

Models	Accuracy	Loss
Proposed Model (epoch 48th)	98.88%	0.0560
MobileNetV2(transfer learning) (epoch 42nd)	95.79%	0.1615
CNN in [2] (epoch 38th)	97.76%	0.0837

Table 3. Comparison of precision across models.

Class \ Metric	Proposed Model	MobileNetV2 (transfer learning)	CNN in [2]
Glioma	0.98	0.94	0.96
Meningioma	0.97	0.91	0.95
Notumor	1.00	1.00	1.00
Pituitary	1.00	0.96	0.99

Table 4. Comparison of recall across models.

Class \ Metric	Proposed Model	MobileNetV2 (transfer learning)	CNN in [2]
Glioma	0.97	0.91	0.95
Meningioma	0.98	0.91	0.95
Notumor	1.00	1.00	1.00
Pituitary	0.99	0.99	1.00

VI. CONCLUSION

In this paper, we build a hierarchical dual-branch CNN model for brain tumor classification. Our model demonstrated excellent performance in distinguishing among different tumor classes and non-tumor images, achieving high accuracy, precision, and recall. Compared to some other methods, the proposed model outperforms the other models in various evaluation metrics on testing dataset, indicating the promise of deep learning methods in the medical domain, particularly in the categorization of brain tumors.

One of the key advantages of our model is its hierarchical and dual-branch architecture, which allows it to extract a richer set of features from the input images. By overcoming the limitations of single-stream CNN architectures, this structure enables more diverse and comprehensive feature representation, ultimately improving learning performance and classification accuracy.

Future studies might concentrate on enhancing the robustness of the model by expanding the dataset and exploring more advanced architectures to improve classification ability and practical applicability in real-world scenarios.

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