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MOBILE NETV1-BASED DEEP LEARNING MODEL FOR ACCURATE BRAIN TUMOR CLASSIFICATION

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ABSTRACT

Brain tumors are among the most dangerous diseases that lead to mortality after a period of time from injury. Therefore, physicians and healthcare professionals are advised to make an early diagnosis of brain tumors and follow their instructions. Magnetic resonance imaging (MRI) is operated to provide sufficient and practical data in detecting brain tumors. Applications based on artificial intelligence contribute a very large role in disease detection, provide incredible accuracy and assist in creating the right decisions. In particular, deep learning models, which are a significant part of artificial intelligence, have the ability to diagnose and process medical image datasets. In this concern, one of the deep learning techniques (Mobile NetV1model) is utilized to detect brain disease from 1265 images gathered from the Kaggle platform. The behavior of this model is studied through four main metrics. This article deduced that this model has a significant effect in diagnosing these images from the most important metric, which is accuracy, as it gained an accuracy result of more than 97%, which is an excellent effect.

Keywords: Mobile NetV1model, Brain tumors, Magnetic resonance imaging (MRI)

1. INTRODUCTION

Brain tumours are now categorised by the World Health Organisation (WHO) as a distinct subtype of malignancies that affect the central nervous system. Studies indicate that Glioma, Meningioma, and Pituitary tumors collectively account for 75% of all brain tumors[1-10]. The degree of malignancy in each of these tumour forms varies. A cancer known as a meningioma can grow on a protective layer which covers the brain's cortex and the vertebral column or the spinal cord[11]. Glioma is a type of brain tumor that originates from glial tissues in the brain and spinal cord. Pituitary tumors, on the other hand, develop in the area of the pituitary gland[13-18].

In recent years, the application of deep learning techniques, particularly convolutional neural networks (CNNs), has changed medical image analysis[19-24]. Among the various fields benefiting from these advancements, brain tumor classification stands out as a critical area where accurate diagnosis is dominant for effective treatment planning. This paper explores the implementation of a Fully Convolutional Neural Network (FCNN) for brain tumor classification, controlling its ability to process information directly from raw image data. On the other hand, DL methods address this issue by using the original image as input.The significance of this study is to improve diagnostic accuracy and efficiency in clinical settings[25-32].

Researchers have been motivated by the challenges of manually reading MRIs and the efficacy of DL techniques in automating disease diagnosis and classification[33]. In such studies, image processing, computer vision, deep learning, machine learning, and object detection have been adopted to develop systems for assisting health experts in the early diagnosis of brain tumors. However, models employing Convolutional Neural Networks (CNN) and their variations have struggled to achieve substantial enhancements in performance. While deep learning techniques, such as CNNs, have yielded remarkable results in various fields, they are often data-hungry, typically requiring a significant number of training samples. Consequently, the challenge of creating an effective, integrated system for contrast enhancement, tumor detection, and classification, even with a limited training dataset remains an open problem.[34-45]

The timely identification of brain cancer is pivotal for successful treatment and rehabilitation[46]. In the realm of IoT healthcare, researchers and medical experts have devised numerous non-invasive techniques for categorizing brain tumors and identifying brain cancer[47]. Computer-based automated diagnostic systems (CADS) created towards the detection of tumours in the brain heavily rely on machine learning (ML) and deep learning (DL) models.In a pioneering Convolutional Neural Network (CNN) architecture named BrainNet is introduced[48]. BrainNet is a specialized system created with the primary objective of accurately classifying and diagnosing brain tumors. The proposed model exhibits rapid and efficient learning, attributed to its smaller number of trainable parameters compared to other architectures [48-52]. The study compared the performance of two models, CNN and fine-tuned ResNet50, for brain tumor classification and detection using MRI images[53-56].

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2. LITERATURE SURVEY

Developed a novel CNN architecture, called BrainNet. This research introduces BrainNet, an innovative Convolutional Neural Network (CNN) architecture specifically designed for the classification of brain tumors into distinct categories.Designed for accurate braintumor classification using MRI images, outperforming established models like VGG16 and InceptionResV2 and limitations was raised on Overfitting risks, dataset dependency, extensive preprocessing needs, limited interpretability, and substantial computational resource requirementsTripty Singh et al. (2024) [1].The purpose of this research is to build an automated, robust, intelligent and hybrid system for the early diagnosis and classifying of brain tumor.The proposed system achieves superior accuracy (98.89%) in brain tumor detection and classification compared to existing models, demonstrating robust performance across varied MRI image contrasts. There is huge scope to optimize the system's performance and reduce the response time for quick and mass screening of brain tumor from different modalitiesMonika Agarwal et al. (2024) [2]. This research presents a CNN model fine-tuned with ResNet50 and made use of a CNN fine-tuned with ResNet50 and integrated with Unet. It achieved very high performance in the tasks of tumor detection and segmentation; however, the effectiveness of the approach might be limited in some sets of data. One limitation of this study could be the dependency on a specific dataset,which might limit the generalizability of the proposed CNN model to other datasets or populationsAbdullah A. Asiri et al. (2023) [3].Feature extraction and classification by incorporating Feature Extraction with Residual Strip Pooling Attention, Atrous Spatial Pyramid Pooling, and a classification module to exclude intra-class variations, which are problematic in small datasets, even though the approach causes heavy demands on computational resources.The proposed method encourages the diagnosis of medical imaging and can solve the problem of large intra-class variations and small-size datasets in medical image classificationAhmed I. Shahin et al. (2023) [4].

3. PROPOSED METHODOLOGY

3.1 Image preprocessing

For a large number of images, the complexity and the computational time increase. The CNN network is used as the images are vectorized in the simple format by observing there features, where the CNN architecture consists of multiple layers, including input layer, convolution layer, fully connected layer, and the output layer. In our proposed model, the input MRI images are resized to 256 × 256 × 1, which refer to width, height, and channel number for images. Then, the convolution layer is represented to capture the low-level features, whereby increasing the number of layers provides high-level features from the input images. These features consist of color, edges, and gradient orientation. The convolution layer consists of a set of convolution kernels, called filters, which convolved with the input to produce the output features.The authors chose the MRI modality for brain tumor detection and classification in this research because these images provide detailed info about the brain soft tissues. However, identifying and localizing a tumor are hindered by the poor visual quality, noise, and low contrast of these images. In rotation, the input images are rotated at angles of 90°, 180°, and 270°, whereas the input image is reflected from horizontal and vertical directions via flipping. The augmentation techniques are useful in providing a large input space to CNNs and reducing the problem of overfitting

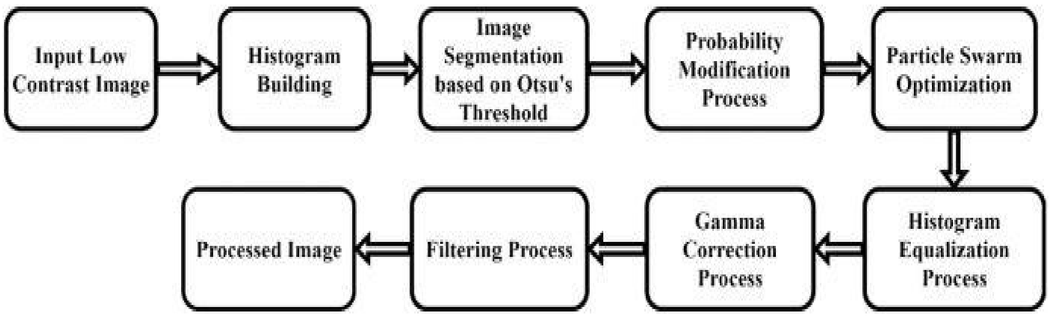

Fig.1 Image Pre-Processing Stage

3.2 Data Preprocessing

Dataset

The dataset used for the study comprises training and testing folders, with each folder containing four subfolders representing the classes: Meningioma, Glioma, no Tumor and Pituitary, as depicted in

Table 1. Train and Test Images

Class	Test set images	Training set images
No Tumor	105	395
Glioma	100	826
Pituitary	74	827
Meningioma	115	822
Overall outcome	**392**	**2870**

Fig.2 The block diagram of the proposed model's general framework

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ALGORITHM

Algorithm: Brain Tumor Classification using FCNN

STEP-1: Start

STEP-2: Input MRI images

STEP-3: Resize the input images from 512×512×1 to 256×256×1

STEP-4: Build the general framework of the proposed FCNN model

STEP-5: For iteration n=1:5
  If n≠1
    model(n) = Load (the trained model (n-1))
  End if
  For fold j=1:5
    Train the model(n) using the Adam optimizer, sparse categorical cross entropy loss function, and early stopping procedure
    Test the trained model using the testing dataset
    Calculate the evaluation metrics
  End for
  Save the trained model
  Compute the mean and standard deviation of the evaluation metrics for the five folds
End for

STEP-6: Output the final trained model

STEP-7: End

4. MODEL EVALUATION

This section discuss the rigorous evaluation protocol employed to assess FCNN performance. This includes metrics such as training and test accuracy, precision, recall, F1-score, and confusion matrices. The proposed model's predictability and robustness are guaranteed by the evaluation procedure. The proposed model was compared against 2 well-known pre-trained benchmark architectures—specifically, ResNet, U-Net in order to assess its efficacy. These benchmark models have been widely used in various image classification tasks and serve as reference points for evaluating the effectiveness of the newly designed CNN architecture. The comparison allows researchers to understand how well the proposed model performs in comparison to well- established and widely recognized models in the field of image classification, helping to validate its performance and potential advantages

4.1 DATASET

The dataset used for the study comprises training and testing folders, with each folder containing four subfolders representing the classes: Meningioma, Glioma, no Tumor and Pituitary, as depicted in. We utilized six datasets in this work to assess our model's performance. Two datasets are utilized for brain tumor detection, two for brain tumor classification into benign and malignant, and two for the classification into glioma, pituitary, and meningioma tumors. All the datasets utilized in this work contain grayscale images of different resolutions.

The training set consists of approximately 394 images in each class, while the testing set contains 2870 images in each class. A training dataset of 105 MRI images and a testing dataset of 395 MRI images make up the benign tumour dataset. There are 2475 MRI images of malignant tumors in the training dataset and 289 MRI images in the testing dataset.

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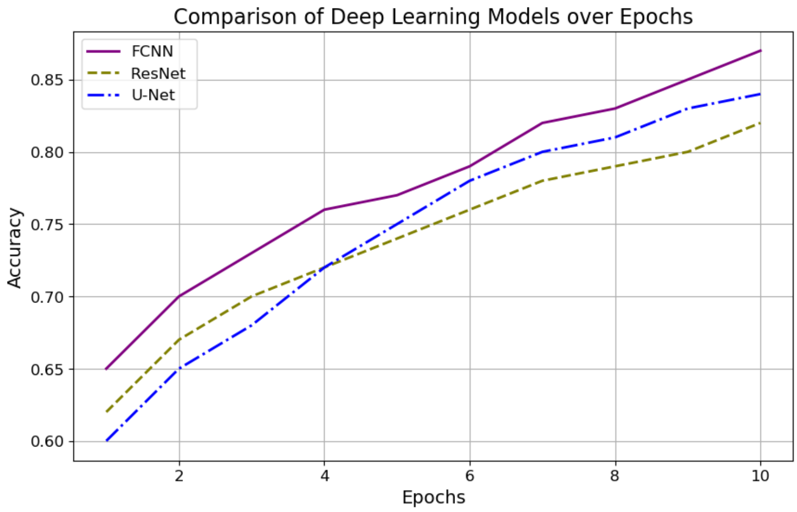
Table 2. Information on the testing and training datasets that are used to classify and identify tumors.

Images Count	Trained Dataset		Tested Dataset	
	Benign	Malignant	Benign	Malignant
294	75	375	205	189

The study on brain tumor classification utilizing a Fully Convolutional Neural Network (FCNN) as a deep learning approach shown remarkable progress in accurately categorizing various forms of brain tumors. The study proved the FCNN model's ability to distinguish between different tumor classifications, showing its potential as a powerful tool in medical image analysis for brain tumor identification. The study's findings highlight the relevance of using FCNN architectures to improve the precision and efficiency of brain tumor classification tasks, which will help progress deep learning applications in medical imaging for brain tumor diagnosis and categorization.

5. RESULT



6. CONCLUSION

This study illustrates the efficacy of using a fully convolutional neural network (FCNN) to classify brain cancers from MRI images. Through thorough experimentation and review, we have demonstrated that the FCNN model not only achieves excellent accuracy in differentiating between distinct tumor types, but also performs consistently across diverse datasets. The use of deep learning techniques, particularly FCNNs, has great promise for expanding the area of medical image analysis, providing doctors with a powerful tool for accurate and rapid diagnosis. Future research directions could include improving the model's interpretability, increasing computational efficiency, andexpanding its applicability to other medical imaging tasks besides brain tumor classification.

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