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Classification of brain tumor of magnetic resonance medical images using convolutional neural network approach

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***Abstract*---**The impact tumours in the brain in medical field cannot be ignored and may lead to a short life in their highest grade. Thus, conduction of proper diagnosis that too in its early stage to improve the quality of life of patients is a necessity. Normally, several image processing tech-niques including Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) is a type of imaging that uses a (MRI) are be ingutilized to localize and calculate the size and tumor in a brain. But has limited performance for accurate quantitative measurements that too in a small number of sample images. In this project, a simple yet robust classification using Convolutional Neural Networks (CNN) for for brain cancer is proposed. The investigational outcomes with low complication is anticipated and potentially competes the relevant state of arts meth-ods.

***Keywords*---**artificial intelligence, convolutional neural network, deep learning, medical diagnosis, medical resonance imaging.

Introduction

Recent expansion in artificial intelligence and information technology techniques is getting popularity in various real life applications. These applications consists medical fields such as brain computing and optimization [1]–[3], development of autonomous vehicles[4]–[7] and progress of smart cities [8]. All these area have uniform weightage but securing life through medical diagnosis is always on the top. Fusion of artificial technique into medical domain has shown remarkable performance over the the old-fashioned method. Brain tumors are among the most serious cancers for extensive illness and death in the US [9]. Common and initial symptom of brain tumor includes mood swings, headaches, change in

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personality, memory loss and vision problem. This ailment keeps the person from basic work, taking a colossal toll on livelihoods and overall progress of society and country because of its severity .A brain tumour is diagnosed by a neurosurgeon or neurologist using a computer tomography (CT) scan and/or magnetic resonance imaging (MRI). However, the anatomy of a tumour in the brain is not uniform and has a wide range of representation. A tumour that has been affected but has not been discovered might sometimes result in mortality. However, due to the brief period of the study, the possibility of a manual error may result in unanticipated treatment. To avoid any problems, a precise detection of such an object 3using intelligent techniques is essential the likelihood of human death.

The advancement of numerous clever approaches in the medical area has aided the exact decision-making of doctors nowadays. a neurosurgeon or a neuropathologist Several image processing and optimization techniques are used in this domain Several ways have been used to comprehend various data patterns applications[10]–[14], but their performance has occasionally been tested against the standard circumstances Recent advances in machine and deep learning have aided in this approach Artificial intelligence (AI)-based systems have benefited from these strategies [15]–[19]. When combined with standards for the improvement of our society, AI techniques have the potential to help with some of the most difficult situations. Deep learning is one of the most recent AI-based techniques that helps to construct robust, accessible, and operative solutions, which can also be applied to the Malaria detection challenge in blood cells. A convolution neural network (CNN)-based model has been used in this suggested strategy to not only effectively categorise afflicted and unaffected brain tumour MRI images, but also to lead the implementation of other illness classification or detection in the same area. The proposed approach is depicted schematically in Figure 1.

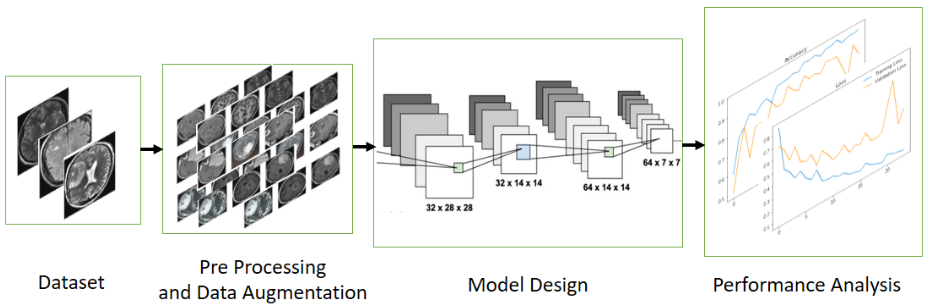


Fig 1. A process flow indicating the classification of brain tumor MRI image into infected and uninfected category

The following is the structure of the remainder of this paper: The relevant studies in the current domain will be discussed in section 2, and the implementation approach and experimental findings will be revealed in section 3. Finally, section 4 reveals the proposed work's performance measure, while section 5 discusses the final observations and includes recommendations for future initiatives.

Related Works

Using various common public datasets, several techniques have been used to classify brain tumours into infected and unaffected parts. The concept of dual path residual CNN was used in this manner, and the model achieved a classification accuracy of 84.9 percent [20]. Similarly, Sajja et al. used an integrated architecture with fuzzy C-means clustering and a support vector machine (SVM) to produce a classification error rate of 5.2 and a 94.8 percent accuracy score [21]. The critical feature was selected using principal component analysis (PCA) and Gray-level co-occurrence matrix (GLCM) to detect the presence of brain tumours and their classification into malignant and benign categories using support vector machine (SVM) [22]. Chan et al. combined VGG16 and ResNet 50 with random forest (RF) and k-means clustering techniques using a typical neural network architecture [23]. The authors had achieved a maximum prediction performance of 86 percent in terms of F1 score. The relevant feature representation was recovered and confirmed by Kaur et al. using a confusion matrix, with SVM score (87.5%) being the highest among KNN, boosted tree, and bagged tree approaches [24]. Veer et al. used a multilayer perceptron mechanism to recover detailed information from MRI images and diagnosed the brain tumour with an accuracy score of 90.47 percent (against an 80 percent -20 percent training and testing dataset)[25]. Kaur et al. suggested a two-stage brain tumour identification method that included morphological operations such as erosion, dilatation, and clustering in the first stage and a nave bayes classifier with an accuracy score of 86 percent [26].

Another feature extraction method utilising CNN is to cluster the mri images using a fuzzy c-means algorithm first [27]. Moreover, the canny edge algorithm is used to detect the tumour region, and CNN was proposed utilizing this two-stage information, with an accuracy of 91.40 percent. Remya et al. extracted the feature extraction and diagnosed the brain tumour using KNN classifier for 250 iterations and attained an accuracy of 85.71 percent [28] utilising contrast stretching and the contouring approach. Ning et al. enhanced the VGG 19 and Inception V3 classical models using data augmentation techniques, followed by detecting and extracting the brain tumour location, and got accuracy scores of 88.96 percent and 91.73 percent for the modified models, respectively [29]. GLCM, shape features, and local binary pattern are computed to estimate the most promising features, and then brain tumor classification is done using RF-PCA, which has a 91.95 percent accuracy [30]. With the advancement of image processing and deep learning techniques, the aforementioned approach has been used. However, by employing an appropriate model design, the performance in classifying infected and uninfected brain tumours can be enhanced. In the study [27], the classification accuracy is promising, but the calculation cost is significant due to the sophisticated CNN design. Obtaining a feature with the least number of models is likewise a viable option. In this study, a CNN-based model for classifying brain tumours into infected and uninfected classes is proposed, with a simpler architecture that is validated by qualitative and quantitative assessment scores.

Material and Methods

The following phases have been addressed in order to perform classification against the brain tumour classifications, and their process flow is shown in Figure 1.

Dataset Collection and Preprocessing

The proposed strategy, which employs a CNN-based classification network, necessitates the use of key features from a standard dataset that can be accessed through a public platform [31]. There are 253 brain MRI pictures in the referred dataset, with 155 images from tumorous afflicted areas and 98 images from non-tumorous areas. Yet, learning important features using a CNN model necessitates a huge amount of data; however, due to a lack of data, a data augmentation strategy was used to enhance the number of data samples and give an appropriate baseline for feature extraction. After the data augmentation process, random rotation, flipping, zooming, brightness variation, and random shift have been applied, yielding 1518 data samples. Figure 2 shows some of the sample photographs from the dataset in question.

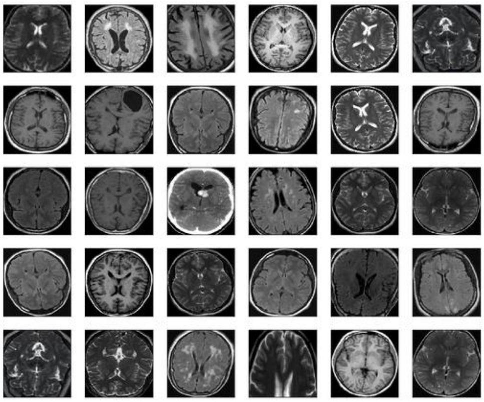


Fig 2. Sample grid of referred brain tumor dataset

Model architecture and Learning

The convolution approach has been provided to the proposed model in order to generate a more notable and robust pool of features. However, increasing the number of convolution operations does not guarantee increased accuracy, since it may be affected by unpredictability or the problem of overfitting and underfitting during learning. Several configurations of significant parameters have been used to maintain the stability between all of the necessary sets of constraints. Following the data augmentation, a total of 11,137 parameters were subjected to the training process, with a kernel size of 32 being functional for the given set of input image sizes in all three (red, green, and blue) channels. A maximum pooling approach has also been implemented to extract the desired features from the input sample and to standardise the valid pixel data. This policy reduces processing complexity by concentrating on high-level feature abstraction, as seen in the equation below.

$$P_{max}(I) = max_u i_u \tag{1}$$

The stimulation values from the occupant pooling area of T-pixels in the image are included in the vector. When the parameters in one layer deviate, the inputs shared with the subsequent levels are shaken. When there are additional layers, changing the input distributions becomes computationally difficult. Batch normalisation is used to reduce this covariate swing, where stabilisation is independent of each stimulus and can be relayed:

$$Mean\ (MiniBatch): \mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{2}$$

$$Variance(MiniBatch): \sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_B)^2 \tag{3}$$

$$Normalize: \hat{x_i} = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{4}$$

$$Scale\ \&\ Shift: y_i = Y\hat{x_i} + \beta \equiv BN_{Y,\beta}(x_i) \tag{5}$$

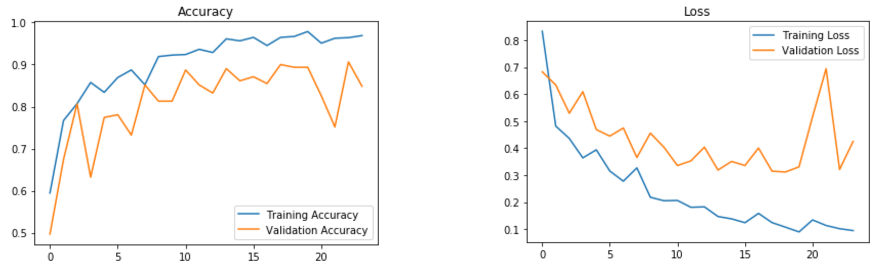
Batch normalization (BN) is used to help the operation of a higher rate of learning by stabilizing the input change. Table 1 shows the configuration details, as well as the output shape and matching parameter number.

Table 1
Configuration details of proposed CNN model

Layer Number	Layer Type	Output Shape	Number of Parameters
1	InputLayer	(None, 240, 240, 3)	0
2	ZeroPadding	(None, 244, 244, 3)	0
3	Conv2D	(None, 238, 238, 32)	4736
4	BatchNormalization	(None, 238, 238, 32)	128
5	Activation	(None, 238, 238, 32)	0
6	MaxPooling	(None, 59, 59, 32)	0
7	MaxPooling	(None, 14, 14, 32)	0
8	Flatten	(None, 6272)	0
9	Dense	(None, 1)	6273

Performance Evaluation

The first 20 epoch sample of learning/training curve with learning rate of.01 has been gathered and exhibited in figure 3 over the modest scheme of the predicted CNN architecture and the operation of numerous layers engaged (a-b). It specifies how the model learns the properties of the provided dataset over time and applies that learning to categorise different forms of brain tumours. Similarly, the early convergence of both the accuracy and loss curves to their maximum and minimum levels, respectively, in a few epochs, has been observed and reveals the perfect performance in both learning and stability.



(a) (b)

Fig 3. Learning curve of proposed brain tumor classifier model. (a) Accuracy. (b) Loss

Aside from the qualitative evaluation stated in Figure 3, standard quantitative stimation [17] was also used to corroborate the suggested approach's optimal behaviour, which is given in Table 2 along with a comparison to several state-of-the-art methodologies.

Table 2
Quantitative classification performance of proposed approach and its comparison with the relevant state-of-the-art technique

Method	Xue[20]	Sajja[21]	Kaur[24]	Veer[25]	Kaur [26]	Remya [28]	Proposed model
Accuracy	84.90	94.80	87.50	90.47	86.00	85.71	95.39

Conclusion

The generated CNN model was created to classify MRI images of brain tumours into infected and uninfected categories, and it achieves a classification accuracy of 95.39 percent by using a simple design and a small number of training epochs. The model was evaluated over qualitative and universal quantitative scores to validate the performance of the suggested strategy. However, with alternative optimizers and unknown data, the model's performance can be further enhanced.

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