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Enhancement of medical images diagnosis using fuzzy convolutional neural network

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ABSTRACT

Brain diseases are primarily brought on by abnormal brain cell growth, which can harm the structure of the brain and eventually result in malignant brain cancer. Major challenges exist when using a computer aided diagnosis (CAD) system for an early diagnosis that enables decisive treatment, particularly when it comes to the accurate detection of various diseases in the pictures for magnetic resonance imaging (MRI). In this study, the fuzzy convolutional neural networks (FCNN) were proposed for accurate diagnosis of brain tumors (glioma, meningioma, pituitary and non-tumor) which is implemented using Keras and TensorFlow. This approach follows three steps, training, testing, and evaluation. In training process, it builds a smart model and the structure consists of seven blocks (convolution, rectified linear unit (ReLU), batch normalization, and max pooling) then use flatten, fuzzy inferences layer, and dense layer with dropout. An international dataset with 7,022 brain tumor MRI images, was tested. The evaluation model attained a high performance with training accuracy of 99.84% and validation accuracy is 98.63% with low complexity and time is 58 s per epoch. The suggested approach performs better than the other known algorithms and may be quickly and accurately used for medical picture diagnosis.

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1. INTRODUCTION

Various clinical uses, such as diagnosis, treatment planning, and surgical navigation, now depend entirely on medical imaging. In order to give medical professionals enough information for clinical objectives [1]. One of the main health issues connected to anomalies [2] in the human brain is [3] a brain tumor [4]. These brain tissues play an important role in the process of brain tumor classification. When used as a tool to support for a surgical operation, computer aided diagnosis (CAD), a neurologist must analyze, classify, and identify the brain tumor [5]. Because the medical field requires effective and trustworthy methods to identify fatal illnesses like cancer, the world's most common cause of patient death [6]. The following elements are responsible for the relevant challenges: i) shape, size, and severity of brain tumors vary widely [7]; and ii) tumors from various disease categories may have a similar appearance [8]. Glioma, meningioma, and pituitary tumors are those with the highest incidence rates of all types of brain cancers [9]. In 2020, according to the World Health Organization (WHO), cancer is the second biggest cause of death globally, accounting for about 10 million recorded deaths [10]. The tumor's stage, the grade and pathological type of the tumor at the time of diagnosis determines the type of treatment to use [11]. Hence, to address this problem automated classification by classifying brain tumor magnetic resonance imaging (MRI) is a possible solution with little intervention from human experts in the relevant sector [12]. In many vision tasks, including detect, image-to-image translations, and semantic segmentation, a branch of artificial intelligence developed from machine learning called deep learning (DL), has prevailed. Over of the past few years, DL health systems have generated a lot of attention and have been heavily utilized in various areas of medicine, from medication identification to clinical [13] decision-making, fundamentally altering the way medicine is practiced [14]. In fact, a number of human illnesses, incorporating COVID-19, heart disease prediction, breast cancer, diabetic disorders, and medical image segmentation [15]. Might be recognized using similar algorithms. The development of AI has opened up a wide range of new scientific issues.

Convolutional neural networks (CNN) is a DL method used to address challenging categorization issues [16] and it is best in feature extraction [17]. CNN is a feed-forward neural network. It facilitates decision-making during illness diagnosis by applying a variety of method, and which makes it simple to forecast and classify the disease [18]. Big data feature learning is accurate and reliable thanks to CNN. They use several samples to get useful information from the data [16]. Fuzzy logic is a powerful technique for simulating human perception and thought. Thus, the fuzzy system and neural networks are merged and the fuzzy rules can be derived from a huge supply of training data by the membership functions of automatically learning [19]. Hence, by combining fuzzy logic with CNN, the fuzzy convolutional neural network (FCNN) is presented. It makes use of the benefits of both CNN and fuzzy logic to classify data in an accurate and reliable manner [20].

The main problem of work is introducing a fully automatic system for diagnosis brain tumors and learning the unique features in images and maximizing the discrimination power without expert guidance which can distinguish between abnormal and normal images on brain MR images with high accuracy and less time complexity. The objectives of this work are building a model that can accurately diagnosis and classify pictures as either brain tumors or not brain tumors to diagnose the infected patients with brain tumors based on the FCNN model that helps the health care center to reduce the time and effort. The FCNN hyper-parameters were tuned to optimize the diagnosis accuracy. The aim of the study, suggested a method a FCNN in automatic diagnosis system if the patients have a tumor of (glioma, meningioma, and pituitary) or not (non-tumor) based on brain MRI images. Using a CNN combined with fuzzy logic in medical images helps in increases of tumor diagnosis and classifying the types of the tumor.

2. RELATED WORKS

As the systems associated to medical images, notably brain tumors, may be recorded based on the diagnostic technology as well as the categorization of their algorithms utilized, several publications have been written to investigate them. It was discovered among the following linked works: according to Pashaei *et al.* [21], classification of meningioma, glioma, and pituitary cancers as three different forms of brain tumors in MRI (contrast-enhanced MRI, CE-MRI) pictures that are T1-weighted. Proposed two techniques, the first of which is CNN, which had four convolutional layers, four pooling layers, one fully connected layer, and several intermediary layers for normalizing data. The classification rate for brain tumors using this approach is 81.09%. The second technique makes use of kernel extreme learning machine (KELM) to categorize these characteristics and CNN to extract features. The result of this method is 93.68%. Deep neural networks have been proposed as a method for classifying MRI scans as “TUMOR DETECTED” or “TUMOR NOT DETECTED,” respectively [22]. In order to do this, features are extracted using a CNN with three layers. This needs very little pre-processing, and the results are produced in 35 epochs using a fully connected network. The model has a 96.08% accuracy rate. Kumar and Mankame [23] introduced an optimized DL mechanism; named dolphin echolocation-based sine cosine algorithm (Dolphin-SCA) based deep CNN. The input MRI pictures are first subjected to pre-processing and followed by segmentation utilizing a fuzzy deformable fusion model and a Dolphin-SCA. The extracted features are used in the deep CNN for performing the brain tumor classification. The proposed technique has accuracy of 0.963. Sharma *et al.* [24] proposed automatic brain tumor detect, by using classification of CNN, the CNN based on transfer learning method using VGG16 (pre-trained model) to classification the brain MRI scans into two classes. Experimental outcomes show the CNN a 90% testing accuracy and 96.5% training accuracy. Rahman and Islam [25] used a CNN to categorize brain cancers in order to make a quick diagnosis. Prior to applying gray scale conversion, input images are first downsized, which helps to simplify the process. Then, in order to differentiate an item from its surrounds, data augmentation is used to improve the data number and enhance the enhanced images, which are then turned into binary pictures. A 96.9% accuracy rate is suggested.

3. METHOD

This work proposed model of FCNN for diagnosis brain tumors in four categories, including (glioma, meningioma, pituitary, and non-tumor). That can achieve by using Google Colab which is based on Python and the Keras library on TensorFlow, is used for the implementation phase. The MR images of size 200×200 (obtained by converting the size of the original image, which has different sizes) are provided as the input to the proposed FCNN model by converting them into three channels. The details of the proposed FCNN model have 26-layer FCNN model. The proposed model aims to multi-class diagnosis, as shown in Figure 1 [26], where brain tumors are diagnoses into four classes. The paper involves multiple steps, starting with the dataset being imported from website. The dataset was subsequently split into training and testing sets. On the dataset, the models were trained. The accuracy of the model was calculated for training and testing.

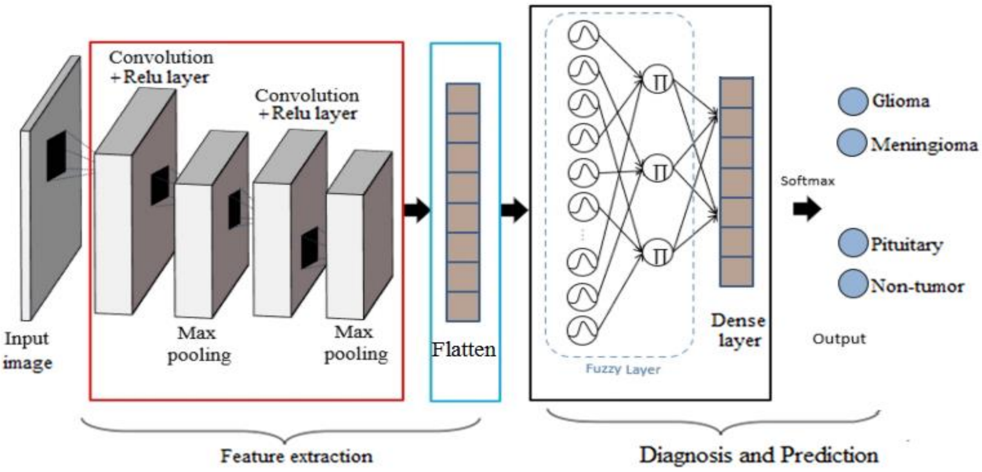


Figure 1. Typical structure of a FCNN

3.1. Magnetic resonance imaging dataset description

The data used in this study consisted of brain MR images from the open access Kaggle dataset [27] included of 7,022 MRI image of the brain. The Google Collaboratory platform is one of Google Research's creations. Data analysis, teaching, and machine learning are three areas where Colab excels. Through the browser, anybody may write and run arbitrary Python code. Colab is just a hosted text editor services that doesn't require installation and gives users free access to computing resources like graphics processing units (GPUs) [28]. The used dataset includes two distinct subsets of brain MRI images, training and testing with subfolders for each class (glioma, meningioma, pituitary, and non-tumor) as shown in Figures 2(a)-(d), which consisted of 1,311 images for the testing set and 5,712 images for the training set. The dataset holds images indicating four types: glioma, meningioma, pituitary and non-tumor as showed in Table 1.

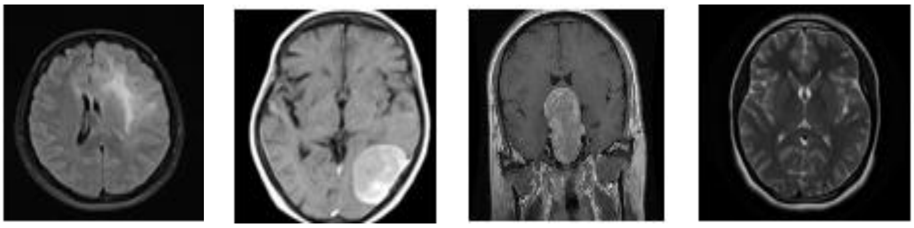

(a) (b) (c) (d)

Figure 2. The brain tumors dataset; (a) glioma, (b) meningioma, (c) pituitary, and (d) non-tumor

Table 1. Dataset description

Dataset of website	Training set	Testing set
Glioma	1,321	300
Meningioma	1,339	306
Pituitary	1,457	300
Non-tumor	1,595	405

3.2. Fuzzy convolutional neural network architecture

Using FCNN, one may examine images with patterns which is accomplished by convoluting to an image and searching for patterns and convoluting over an image. CNNs are quite good at identifying things in pictures [29]. The proposed model uses FCNN to diagnosis brain tumor from MRI images. The convolutional layer, pooling layer, fuzzy layer, and fully connected layer make up structure of FCNN. The suggested model's convolution layer is crucial since it is in charge of extracting features from the MRI image. After the convolutional layer, a pooling layer reduces the image dimensions depending on the feature to produce a new feature image and reduce the network parameters. The commonly applied average pooling or max pooling strategies are used for the feature extraction with the previous convolution layer. The rectified linear unit (ReLU) layer performs element-by-element activation. ReLU function inserts all pixels from the image, and if negative values exist, it converts these to zero [30]. Fuzzy layer aids in decision-making for tumor diagnosis and increases precision. In the final layer, fully connected layer is used to perform diagnosis process of FCNN.

3.3. Evaluation metrics

For the evaluation of FCNN model, a metric is accuracy. The percentage of accurate predictions of a model is how accuracy is defined. A true negative (TN) values and a true positive (TP), which denote successfully diagnosed aberrant brain pictures and normal brain images respectively, are categorized as correct. False positives (FP) and false negatives (FN) are categorized as inaccurate, with FP showing incorrect pictures of the usual brain and FN denoting incorrect images of the diseased brain [31], respectively. We assessed the precision of our suggested model using [32]:

$$Accuracy = \frac{number\ of\ correct\ predictions}{total\ number\ of\ predictions} \tag{1}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

4. MODEL ARCHITECTURE

The suggested design is composed of seven blocks, the first six of which are convolutional parts and the final one being a diagnostic component. Resizing was used in block 1 to generate an input of shape for MRI images that is 200×200×3, converting all of the images into a single dimension, convolutional layers are used with 128 filters of size 7×7 using the ReLU function, batch normalization layers permit the deep neural network's training process to continuously distribute inputs to each layer. This consistency might differ from the parameters of the preceding layer, which makes it difficult to maintain and slows down training since it necessitates proper initial of a parameters and then a lower learning rate. By normalization layer inputs, which is accomplished it after every convolutional layer and fully connected layer, it is possible to avoid the difficulties in training FCNN architecture with a nonlinearity saturation feature, known as an internal covariate shift. Each trained mini-batch undergoes this normalization procedure as part of the general FCNN architecture. Batch normalization is used after activation layers (ReLU function) and finally max-pooling layers of 2×2 dimensions are used after batch normalization layers. in blocks 2 and 3 the convolutional layers are used with 128 filters of size 7×7 using the ReLU function, batch normalization layers and finally max-pooling layers of 2×2 dimensions. In blocks 4 and 5, the same blocks 2 and 3 are used but the number of filters is change to 256 instead of 128 filters. The same as explained above in block 6 but the number of filters is change to 512 filters. So, six convolutional layers, six max-pooling layers, and six batch normalization layers make up this convolutional part's structure.

In diagnosis part, flatten layer are used to make the 2D arrays input 1D and layer named fuzzy_inference_block that helps us in the decision-making process of diagnosing and three dense layers are used, the first has 1,024 output perceptron's employing ReLU, the second dense has 512 output perceptron's employing ReLU and dropout layer is placed behind these dense layers (was set to 0.25). The third dense layer is final layer of the model with four perceptron's to perform the diagnosis and prediction process of each image in the four classes (glioma, meningioma, pituitary, and no tumor) by a function (softmax) as shown in Figure 3. The training was stopped after 56 epochs. Different hyper-parameters are used with the FCNN model. The hyper-parameter settings for the FCNN model are displayed in Table 2.

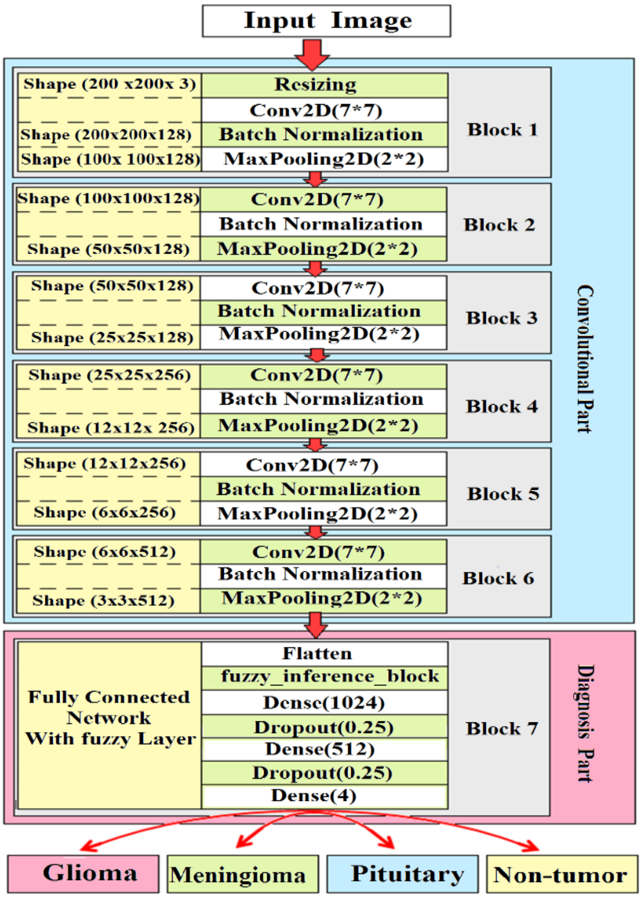


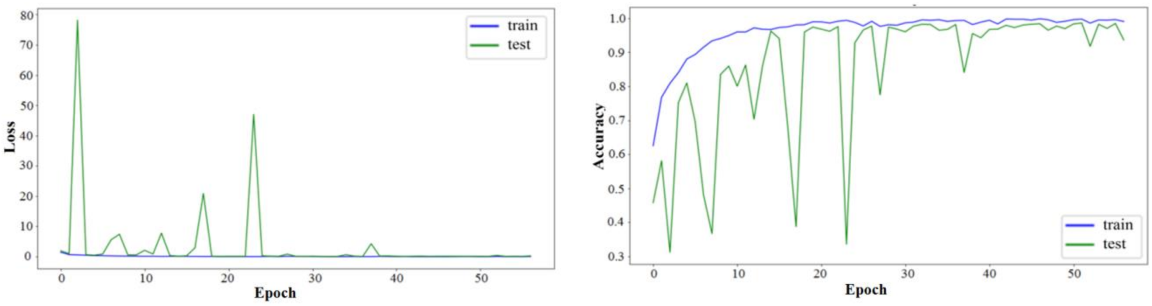
Figure 3. The structure of the FCNN model architecture

Table 2. The developed FCNN model hyper-parameter

Hyper-parameter	Settings
Dropout rate	0.25
Filter size	(7, 7) (128, 128, 128, 256, 256, 512)
Learning rate	0.002
Loss function	Categorical-crossentropy
Number of convolution layer	6
Number of epochs	100
Number of fully connected layer	3(1,024; 512; 4)
Number of max poling layer	6(2, 2)
Optimizer	Adam

5. RESULT AND DISCUSSION

In the Python-based Google Collaboratory platform, which can operate with GPUs, was employed in this work. On four classes, the proposed FCNN model's performance is evaluated. The brain tumor MRI dataset is divided during the experiment into an 80% for training (5,712 pictures) and a 20% for testing (1,311 images). The 4 kinds of brain diseases may be identified and diagnosed by the FCNN with 99.84% accuracy and 0.0064 loss. The findings of the FCNN model's brain tumor diagnosis are displayed in Figure 4. The accuracy and loss per epoch curves for the training and validation tests using the brain tumor MRI image dataset are shown in Figures 4(a) and (b), respectively. It was proven that the FCNN model outperformed others in diagnosing brain cancers by maintaining higher values close to one. Table 3 displays the amount of time, the training accuracy, the training loss, as well as the suggested model's validation accuracy and validation loss. Following the training procedure, we recorded the weights of each model. Therefore, in order to identify the tumors in a particular MRI image, we don't need to repeat the training procedure. The average training duration per one epoch is 59 and 58 seconds. Finally, we conducted a comparison of our suggested method findings with those of other research publications that focused on the same ailment and algorithm, as shown in Figure 5. Our suggested technique provided an accurate result diagnosis of brain tumors in few times and without any processing of medical images.



(a) (b)

Figure 4. The brain tumors diagnosis results of the FCNN model (a) the curves of loss (per epoch) and (b) the curves of accuracy (per epoch)

Table 3. Training and validation accuracy on FCNN

Epoch	Time elapsed (s)	Loss	Training accuracy	Validation loss	Validation accuracy
1	82	1.4442	0.6252	1.9191	0.4577
2	58	0.6707	0.7680	0.9902	0.5812
3	58	0.5578	0.8088	78.1490	0.3120
4	58	0.4712	0.8403	0.6204	0.7521
5	58	0.3292	0.8801	0.4570	0.8101
9	59	0.1797	0.9407	0.5584	0.8345
12	58	0.1312	0.9597	0.8369	0.8627
15	58	0.1113	0.9669	0.1165	0.9626
20	58	0.0372	0.9897	0.1032	0.9741
23	58	0.0309	0.9912	0.1213	0.9756
31	58	0.0543	0.9865	0.1534	0.9603
33	58	0.0194	0.9954	0.0598	0.9825
37	58	0.0248	0.9933	0.0846	0.9817
43	58	0.0081	0.9977	0.1375	0.9794
44	58	0.0121	0.9970	0.1753	0.9725
45	58	0.0082	0.9970	0.1052	0.9802
46	58	0.0182	0.9947	0.1460	0.9825
47	58	0.0064	0.9984	0.1415	0.9840
51	58	0.0131	0.9960	0.1214	0.9832
52	58	0.0169	0.9974	0.1013	0.9863
54	58	0.0219	0.9951	0.0937	0.9825
56	58	0.0177	0.9961	0.1090	0.9847

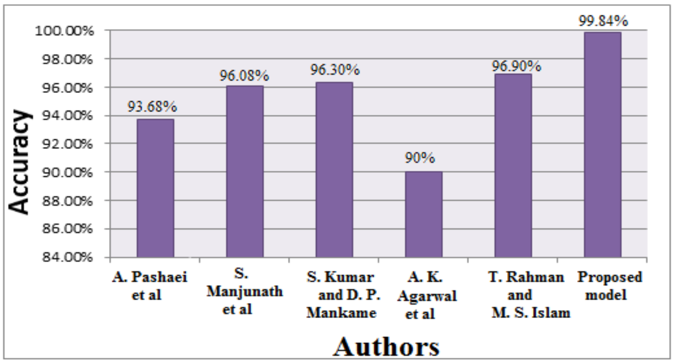


Figure 5. Comparison of the proposed model with other work

6. CONCLUSION

The major objective of this research is to develop a rapid, accurate, high-performing, low-complexity, and time-efficient automatic brain tumor diagnosis system. The FCNN for brain tumor diagnosis which can predict tumor types accurately was used. Also, the diagnosis results are given as tumor or non-tumor. Google Colab was used for implementation brain tumor MRI dataset from website. Finally, the training accuracy, training loss, validation accuracy and validation loss calculated. The training accuracy is 99.84% and the validation accuracy is 98.63%. In the view of an impressive performance of FCNN may be used successfully by medical professionals for diagnostic reasons in order to identify brain tumors in both children and adults as early as possible. The highly accurate diagnostic results can be produced fast by processing a large number of MRI images quickly. Future research will expand on this to identify and categorize various brain strokes by examining various brain tissue patterns.

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