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Convolutional Neural Networks Grid Search Optimizer Based Brain Tumor Detection

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Abstract: The brain tissues segmented by MRI and CT provide a more accurate viewpoint on diagnosing various brain illnesses. Many different segmentation approaches may be used to brain MRI images. Some of the most successful include Histogram thresholding, area based segmentation (K-means, Expectation and Maximization (EM), Fuzzy connectivity, and Markov random fields (MRF). The Hidden Markov Random field (HMRF) approach is one of the most effective segmentation techniques available. It is capable of solving quickly distinct brain tissues for recognition purposes. Using the HMRF model allows for the reduction of energy consumption and the smoothing of images. In this work, the primary goal is to increase segmentation quality by implementing a unique Hidden Markov Random field model and employing MATLAB simulations to implement in Spatial Fuzzy, Iterative Conditional Mode (ICM) method, Fuzzy MRF technique, and Hidden Markov Random field model. The results will be compared to those obtained using Histogram thresholding, the Region Growing method (RGM), the k-means methodology, and the Expectation and Maximization methods to assess segmentation quality and noise reduction.

Keywords: Brain tumor detection, Deep learning, Convolution neural networks, Hidden markov random field.

1. Introduction

Brain tumors are defined as masses created by aberrant multiplication of brain cells that have gotten rid of the brain's regulating systems. They are the most common kind of tumor [1]. Tumors that develop in the skull have the potential to expand, exert pressure on the brain, and harm overall health. The early identification and categorization of brain tumors is a significant study topic in the area of image segmentation, and it aids in selecting the high appropriate technique to save the lives of people suffering from the disease [2].

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Tumors of the brain may be categorized in a variety of different ways. For example, one of the most often used categorizations is to divide brain tumours into two categories: benign and malignant [3]. Because they have not spread to the brain surrounding tissue, they could be eliminated after surgical treatment. Tumours which are produced in the pituitary gland brain benign tumours are tumours that originate within the skull but outer area of the brain matter and are generally painless [4]. Meningioma's are a significant component of this category. Brain benign tumours, in contrast to benign tumours in other organs, may sometimes result in life-threatening diseases. Some benign tumours may develop into malignant tumours in rare cases [5]. Pituitary tumours are so named because they are often found in the pituitary gland, which controls hormones and regulates processes in the body.

Pituitary tumours are classified as benign tumours since they do not spread to remaining areas of the body. Because they are benign, they very rarely recur as malignant tumours. Pituitary tumour problems may result in long term hormone insufficiency as well as eyesight loss in certain people. Those who have malignant tumours have aberrant cells that multiply uncontrollably and irregularly. These tumours can compress, infiltrate, and Emrah Irmak many regions of the body [6]. Even though the majority of pituitary tumours or normal tissues are destroyed. It is sometimes referred to as metastatic brain tumours when the tumour first appears in another section of the body and then spreads to the brain. The stomach, lung, large intestine, skin, breast and prostate are the common general sites of genesis for these cancers. Gliomas are the most prevalent kind of malignant tumour in the brain [7]. They are reason for most brain malignancies because they include cells that proliferate uncontrollably. Even though they seldom spread to the spinal cord or even other organs of the body, they develop swiftly and may expand into the healthy tissues in their immediate surroundings. Gliomas are further subdivided into grades, which are the severity of the tumour.

The WHO grading procedure for glioma tumours is now the most commonly recognised categorization system for glioma tumours [8]. The WHO grading system divides gliomas into four classes, ranging from grade I to grade IV. Because of their propensity to infiltrate other brain structures, they need additional medicinal measures in addition to surgical surgery to be effective [9]. Finally, Grade IV tumours are recognized for being the fastest-growing tumours, and as such, they need the most strong treatment procedures. Early detection, accurate grading, and categorization of brain tumours are critical in cancer diagnosis, treatment planning, and outcome assessment. The identification, categorization, and grading of tumours in the brain are still based on histopathological diagnosis of biopsy specimens, despite the breakthroughs in medical technology that have occurred in recent years. The definitive diagnosis is generally reached after a thorough clinical examination and interpretation of imaging modalities such as MRI or computed tomography (CT), followed by pathological testing [10]. It is well-known that the most significant drawbacks of this diagnostic approach are that it is intrusive, time-consuming, and prone to sample mistakes, among other things. It is possible to improve the diagnostic abilities of clinicians and radiologists by utilising computer-aided fully automated detection and diagnosis systems that are designed to make fast and accurate decisions by experts [11-12]. This will reduce the time it takes to make a correct diagnosis and save money.

This research aims to develop three completely automated CNN models for multi-classification of brain tumours using publically accessible datasets, with each model being totally automatic. The author believes that this is the first effort at multi-classification of brain cancers from supplied MRI images using CNN, which has almost all hyper-parameters automatically adjusted by the grid search optimizer, to the best of his knowledge. The remaining article is organized as follows. Section 2 presents the materials and methods, section 3 about results and lastly in section 4 the conclusions are drawn.

2. Materials and Methods

2.1 Data set

A total of four separate datasets, all of which were sourced from publically accessible sources, were utilized in this investigation. The reference image database to assess treatment response (RIDER) is the name given to the first dataset in this series [11]. The RIDER dataset is a focused data collection consisting of MRI-multi-sequence pictures from 19 patients with glioblastoma that was created with the help of the National Cancer Institute (Grade IV) [12]. In this collection, a total of 70,220 photographs have been collected. In the second dataset, REMBRANDT stands for the Repository of Molecular Brain Neoplasia Data (Repository of Molecular Brain Neoplasia Data) [13]. The REMBRANDT dataset comprises MRI multi-sequence pictures from 130 individuals with glioma of Grade II, Grade III, and Grade IV, all of whom were diagnosed with the disease. It is worth noting that there are 110,020 photos in total in this collection. The third dataset is referred to as the Cancer Genome Atlas Low-Grade Glioma (TCGA-LGG) collection [13]. In the TCGA-LGG data collection, there are 241,183 magnetic resonance scans of 199 individuals with low-grade glioma (LGG) (grade I and grade II). They are from the tumor imaging archive (TCIA) project, a cancer imaging data repository [14]. Each instance had T1-contrast-enhanced and FLAIR pictures in addition to the standard images. It was also utilized in this investigation.

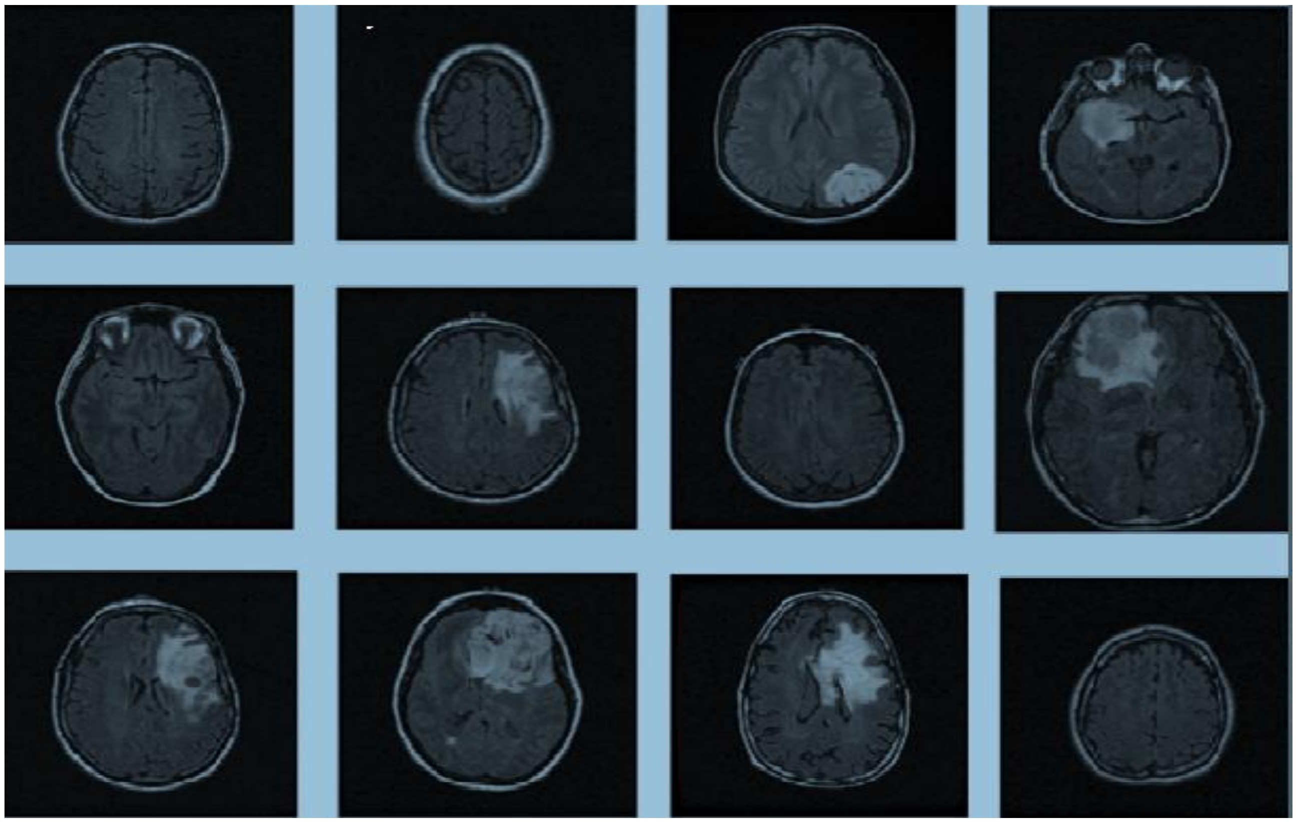

Fig. 1: Samples of brain tumor MRI images

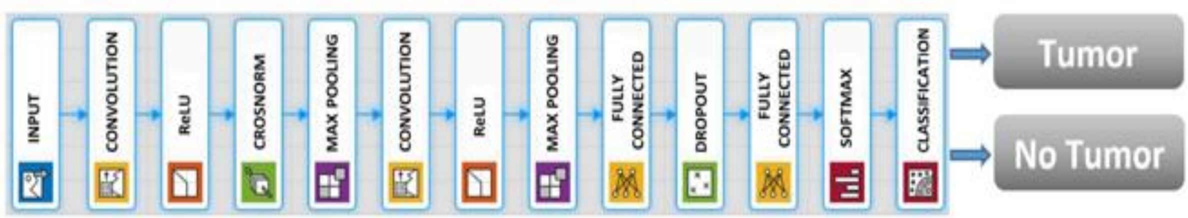

Fig. 2: Model of the suggested CNN

Fig. 3: Model of the suggested CNN network for segmentation-2 task

Another dataset [15-16] comprises 3064 T1-weighted contrast-enhanced images from 233 individuals with three types of brain tumor: glioma (1426 slices), meningioma (708 slices), and pituitary tumors (930slices). Some of the samples from the data repository are shown in Fig. 1. A total of 2990 photos are gathered for the Classification-1 job, with 1640 tumor images and 1350 non-tumor images being included. A total of 3950 photos are gathered for the Classification-2 job, comprising 850 normal images, 950 glioma images, 700 meningioma images, 700 pituitary images, and 750 metastatic images. A total of 4570 photos are gathered for the Classification-3 assignment, with 1676 images classified as grade II, 1218 as grade III, and 1676 as grade III.

2.2 Convolution neural networks

The CNN is the deep learning model most widely employed among neural networks. Each CNN mode has two parts: feature extraction and classification, which are both performed in parallel. The input layer, the convolution layer, the pooling layer, the fully connected layer, and the classification layer are the five primary layers of a CNN architecture, which are described below [6]. CNN accomplishes feature extraction and classification with the use of successively trainable layers that are put one after the other in a pyramid-like configuration. The convolutional and pooling layers are often included in the feature extraction component of the CNN, while the fully connected and classification layers are typically included in the classification section. In recent years, CNNs have mostly focused on image classification and accepted pictures as input data; however, they have also been extensively employed in a broad range of other disciplines in which the input data may be any signal, such as audio and video [11]. Figs. 2 to 4 show this research's designed CNN models for specific tasks.

2.3 Performance discussion

It is critical to assess the segmentation performance of image separation research to provide scientific support for the investigation's findings. The categorization research will remain unfinished and intellectually unsound unless this is done. A variety of performance evaluation metrics have been used in picture classification studies for a long time and have become standard performance evaluation metrics in other research of a similar kind. Accuracy, specificity, sensitivity, and precision are the three characteristics. As in previous image classification studies, these metrics are utilized to evaluate the accuracy and reliability of the classification process in this work. These metrics are widely acknowledged as standard performance assessment metrics in the image classification field. Furthermore, the area under the receiver operation characteristic curve (ROC), also known as the AUC of the ROC curve, is used to assess the performance of the models. The corresponding formulas for each of these metrics and the relationship between them. True positive, true negative, false positive, and false negative are the acronyms for true positive, true negative, false positive, and false negative, respectively.

2.4 Hyper parameter optimization

There have been some issues in the usage of CNNs in the area of image segmentation as a result of the rising use of CNNs in this discipline [6]. As the depth of the architectures, which are being built in order to get more effective outcomes, increases, and the quality of the input pictures improves, the computing costs climb in proportion. Increased success occurs from the use of powerful hardware as well as optimization of the hyper-parameters of the created network. Both reductions in computing costs and accomplishment of more successful outcomes largely depend on the usage of powerful hardware. As a result, the grid search optimization approach is used to automatically tune practically all of the proposed CNN models' critical hyper-parameters, saving time and effort. When the value range of a CNN's hyper-parameter optimization is limited, the grid search optimization approach provides an efficient alternative to traditional optimization. Convolutional layer activations for classification-1 task is depicted in Fig. 5. With the grid search, the goal is to find the optimal combination of which the network has been taught in all of the possible range combinations. CNN models are very complex designs that include a large number of hyper-parameters.

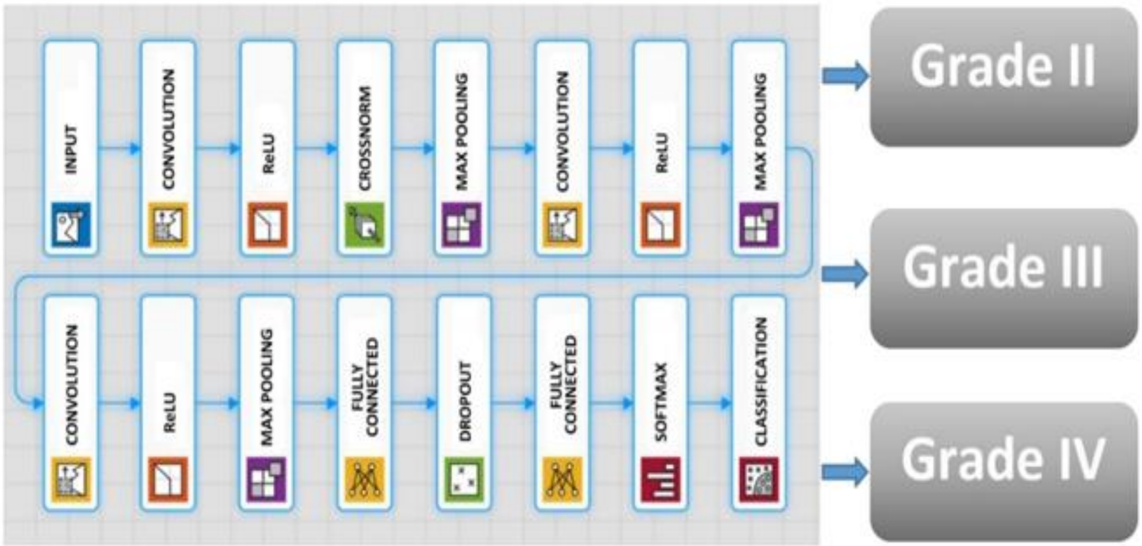

Fig. 4: Architecture of the suggested CNN model

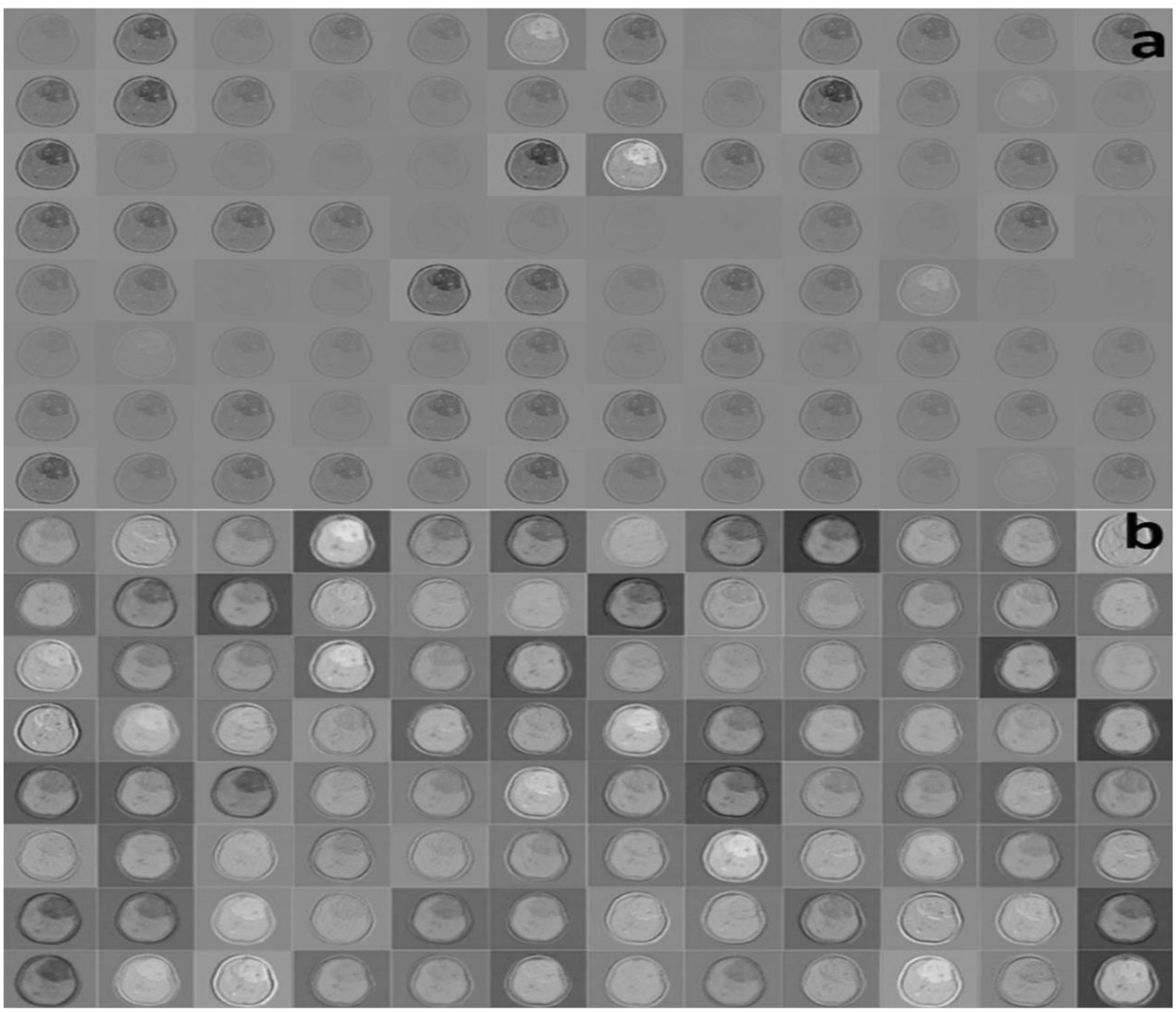

Fig. 5: Convolutional layer activations for classification-1 task.

The architectural hyper-parameters and the fine adjustment hyper-parameters are the two types of hyper-parameters that are most often encountered. The architectural hyper-parameters include the number of convolutional pooling layers, the number of fully connected layers, the number of filters, the size of the filters, and the activation function. Fine adjustment hyper-parameters, on the other hand, include l2 regularization, momentum, mini-batch size, and learning rate, to name a few examples.

3. Results

A fivefold cross-validation approach for the Classification 1 task is used to assess the effectiveness of the suggested model's performance. The dataset is separated into five sets, four of which are used for training and one of which is used for testing. Four of the sets are used for training and one is used for testing. The trials are carried out five times in total. It is necessary to assess each fold's classification performance to obtain the model's average classification performance for the job at hand. High accuracy from the training and validation stages is meaningless until the trained and hyper-parameter-tuned CNN is tested on unknown data to determine its predictive ability. White pixels in Fig. 6 (c) show strong activations which shows that this channel is strongly activated at tumor position. The accuracy and loss curves for Classification-1 task are depicted in Fig.7. To assess the effectiveness of trained CNN on predicting samples, a test dataset is randomly allocated and segregated from the training and validation datasets; otherwise, the high accuracy might be attributable to erroneous dataset selection (e.g., obvious images with strong characteristics from severe tumor patients).

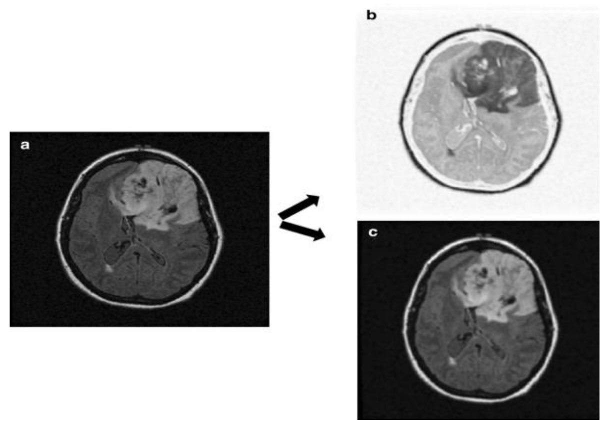

Fig. 6: White pixels in *c* show strong activations which shows that this channel is strongly activated at tumor position

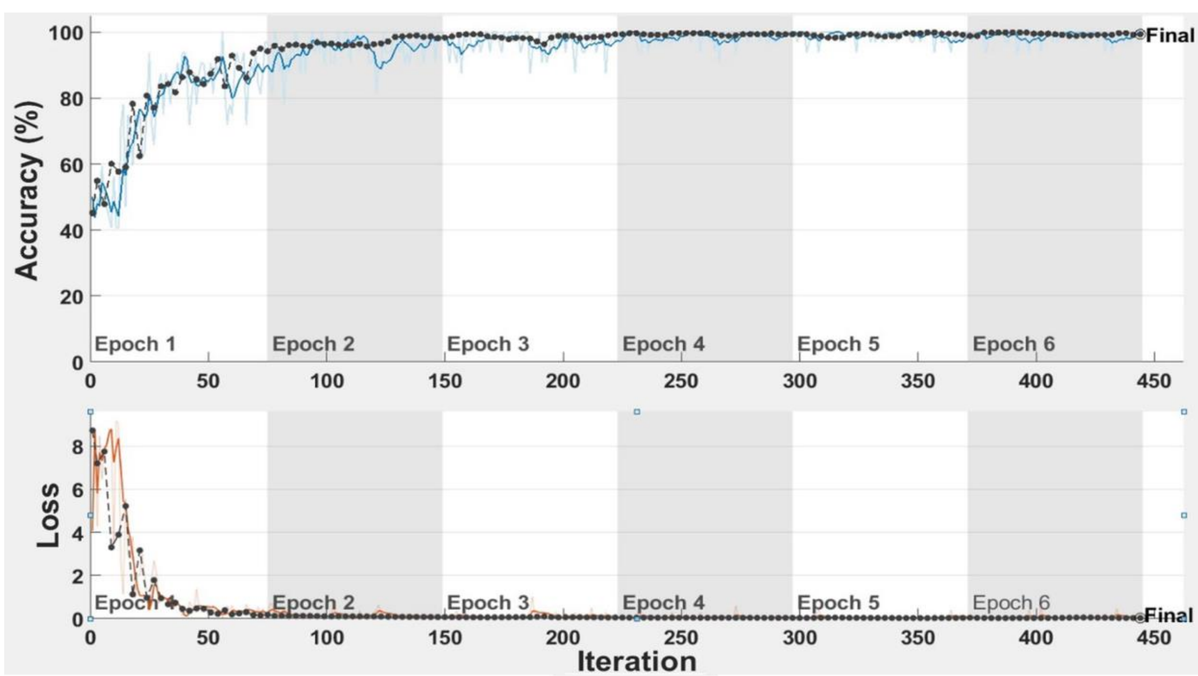

Fig. 7: Accuracy and loss curves for Classification-1 task

The results shows the picture distribution for the Classification-1 task. Because the research contains 2990 samples, there are enough images to be randomly divided into three groups: training, validation, and test sets, with a ratio of 60:20:20 as indicated in the table. Twenty-nine photographs from each class are randomly omitted from the dataset, and these images are utilized for testing reasons only.

4. Conclusion

In recent years, image categorization using convolutional neural networks has become more popular in identifying medical disorders. It is neither conceivable nor reasonable to develop an efficient CNN model that can be used with other classification models to get excellent results across the board. This is why each issue type has its own CNN model created specifically for it. The CNN model's structure and complexity may differ significantly depending on the kind of issue, the inputs, and the predicted outputs. This work develops three separate CNN models for three different categorization goals, each with its own set of parameters. The first model is intended to identify brain tumors using MRI pictures provided as input. The second model is intended to determine the kind of brain tumor, and the third model is intended to forecast the grade of the brain tumor, respectively. One of the issues faced while using convolutional neural networks is determining which network model would be the most effective for the current task. It is proposed in this work to utilize a grid search optimizer to create the most successful CNN model and to optimize the hyper-parameters of the CNN model in order to improve performance. Large clinical datasets that are freely accessible are used to generate satisfactory categorization results for the patients. For example, using the first created CNN model, it is possible to identify brain tumors with a 99.33 percent accuracy, which is really good in this case.

Conflict of Interest

The authors declared "No conflict of interest"

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