Deep Convolutional Neural Network On Brain Tumor MRI Images Using

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Abstract: The histological examination of biopsy tissues is still used in the diagnosis and categorization of brain tumours today. It is now necessary to use an intrusive, time-consuming, and prone to human mistakes technique. These drawbacks demonstrate how critical it is to develop a completely automated technique for multi-classification of brain tumours that is based on deep learning to overcome them. The objective of this research is to develop a multi-classification system for brain cancers for the purpose of early diagnosis via the use of convolutional neural networks (CNN). In this paper, three distinct CNN models are presented to be used for three different classification challenges. A brain tumour may be detected with 99.33 percent accuracy using the first CNN model, which was developed by Google. The second CNN model can accurately categorise brain tumours into five types: normal, glioma, meningioma, pituitary, and metastatic. The accuracy of the second CNN model is 92.66 percent, and it can distinguish between normal and glioma. In the third CNN model, there are three categories of brain tumours that can be classified with accuracy of 98.14 percent. These are Grade II, Grade III, and Grade IV tumours. The grid search optimization approach is used to automatically identify all of the critical hyper parameters of CNN models. It has been reported before that this is the first work to investigate multi-classification of brain tumour MRI images using CNN, with practically all hyper-parameters optimised using the grid search optimizer, to the best of the author's knowledge. The suggested CNN models are compared to other prominent state-of-the-art CNN models, such as AlexNet, Inceptionv3, ResNet-50, VGG-16, and GoogleNet, as well as other popular CNN models from the literature. Large clinical datasets that are freely accessible are used to generate satisfactory categorization results for the patients. The suggested CNN models may be used to help doctors and radiologists in confirming their initial screening for brain tumour multi-classification purposes, and they can also be used to aid in the development of new CNN models.

Keywords: Convolutional Neural Network, Deep learning, Brain tumors, Tuberculosis

1 Introduction

Brain tumours 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 tumour. Tumors that develop in the skull have the potential to expand, exert pressure on the brain, and have a negative impact on overall health. The early identification and categorization of brain tumours is a significant study topic in the field of medical imaging, and it aids in the selection of the most appropriate treatment technique to save the lives of people who are suffering from the disease. Tumors of the brain may be categorised in a variety of different ways. For example, one of the most often used categorization kinds is to divide brain tumours into two categories: benign and malignant tumours. Because they have not spread to the surrounding brain tissue, they have a good possibility of being removed after surgery. Tumors that begin in the pituitary gland Brain benign tumours are tumours that originate within the skull but outside of the brain matter and are normally painless. Meningiomas 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 (for example, meningiomas) may develop into malignant tumours in rare cases. 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 other parts 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 have the ability to compress, infiltrate, and Emrah Irmak many regions of the body. Despite the fact that 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 lung, breast, large intestine, stomach, skin, and prostate are the most common sites of genesis for these cancers. Gliomas are the most prevalent kind of malignant tumour in the brain. They are responsible for the majority of brain malignancies because they include cells that proliferate uncontrollably. In spite of the fact that 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 World Health Organization (WHO) (Banan and Hartmann 2017) grading system for glioma tumours is now the most commonly recognised categorization system for glioma tumours. The WHO grading system divides gliomas into four classes, ranging from grade I to grade IV (from benignant to malignant) (Kleihues, Paul,nBurger and Scheithauer1993). Because of their propensity to infiltrate other brain structures, they need additional medicinal measures in addition to surgical surgery to be effective. Finally, Grade IV tumours are recognised for being the fastest growing tumours, and as such, they need the most severe treatment methods (National Cancer Institute 2020). 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. After a thorough clinical examination and interpretation of imaging modalities such as magnetic resonance imaging (MRI) or computed tomography (CT), followed by pathological testing, the definitive diagnosis is generally reached. 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. This will reduce the amount of time it takes to make a correct diagnosis and will save money. In this research, the goal is 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.

2 Related work

Recent study has focused on brain tumour categorization using machine learning techniques, which has been researched extensively by researchers over the last several years. A significant influence has been made in the area of medical image analysis, particularly in the field of illness detection, as a result of the development of artificial intelligence and deep learning-based new technologies (Mahmoud et al. 2020, 2021;Yaqub et al. 2020). Parallel to this, several research have been undertaken on the identification and classification of brain tumours using CNN, as well as on the multiclassification of brain tumours. This section is dedicated to a review of the literature on the multi-classification of brain tumours using CNN. It is feasible to look at the research in the literature from a variety of perspectives. For example, there are researchers who have accomplished brain tumour classification using CNN models that they have developed themselves, as well as researchers who have used the transfer learning technique to accomplish the same goal using the same CNN models. Each of the researchers listed below has created their own CNN models for the categorization of brain tumours. Utilizing 3064 T1-weighted contrast enhanced MRI images, Badza and Barjaktarovic's 2020 developed a 22-layered CNN architecture for brain tumour type classification using a 22-layered CNN architecture. Their suggested model was successful in accurately classifying the brain tumour as meningioma, glioma, or pituitary with 96.56 percent accuracy, according to the researchers. According to another work, Mzoughiet al. (2020) proposed a deep multi-scale 3D CNN model for brain tumour grading from volumetric 3D MRI images using deep multi-scale 3D CNN models. The suggested technique had a classification accuracy of 96.49 percent when it came to distinguishing between low-grade glioma and high-grade glioma in brain tumour pictures. Ayadi et al. (2021) proposed a computer-assisted diagnostic (CAD) approach for brain tumour categorization that was based on the CNN. Three separate datasets were used in the experiments, which were conducted using the 18-weighted layered CNN model. The results showed that the model obtained 94.74 percent classification accuracy for brain tumour type classification and 90.35 percent classification accuracy for tumour grading. 2018 saw the publication of Pereira et al. (2018), who employed CNN to predict tumour grade directly from imaging data, so eliminating the requirement for expert annotations of areas of interest. They looked at two different prediction approaches: 1016 Iranian Journal of Science and Technology, Transactions of Electrical Engineering (2021) 45:1015–1036123 from the whole brain and from a tumour location that was automatically designated by the computer. With the grade prediction from the entire brain, they acquired an accuracy of 89.5 percent, and with the grade prediction from the tumour ROI, they reached an accuracy of 92.99 percent. According to Abiwinanda et al. (2019), they applied the simplest feasible architecture of CNN to detect three most prevalent forms of brain malignancies, namely, the glioma, meningioma, and pituitary tumour, with a validation accuracy of 84.19 percent at the highest level of accuracy attainable.

3 Materials and Methods

3.1 Dataset

A total of four separate datasets, all of which were sourced from publically accessible sources, were utilised in this investigation. The reference image database to assess treatment response (RIDER) is the name given to the first dataset in this series (Barboriak2015). 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). 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) (Lisa et al. 2015). 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 (Pedano et al. 2016). In the TCGA-LGG data collection, there are 241,183 magnetic resonance scans of 199 individuals with low-grade glioma (LGG) (gradeI and grade II). They are from the tumour imaging archive (TCIA) project, which is a repository for cancer imaging data (Clark et al. 2013). Each instance had T1-contrast-enhanced and FLAIR pictures in addition to the standard images. It was also utilised in this investigation. Another dataset (Cheng et al. 2015) comprises 3064 T1-weighted contrast-enhanced images from 233 individuals with three types of brain tumour: glioma (1426 slices), meningioma (708 slices), and pituitary tumours (930slices). Some of the samples from the data repository are shown in Figure
1. A total of 2990 photos are gathered for the Classification-1 job, with 1640 tumour 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 images classified as grade III, and 1676 images classified as grade III.

3.2 Convolutional Neural Networks

The CNN model is the deep learning model that is 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. 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 (Dog antekinetal, 2019).

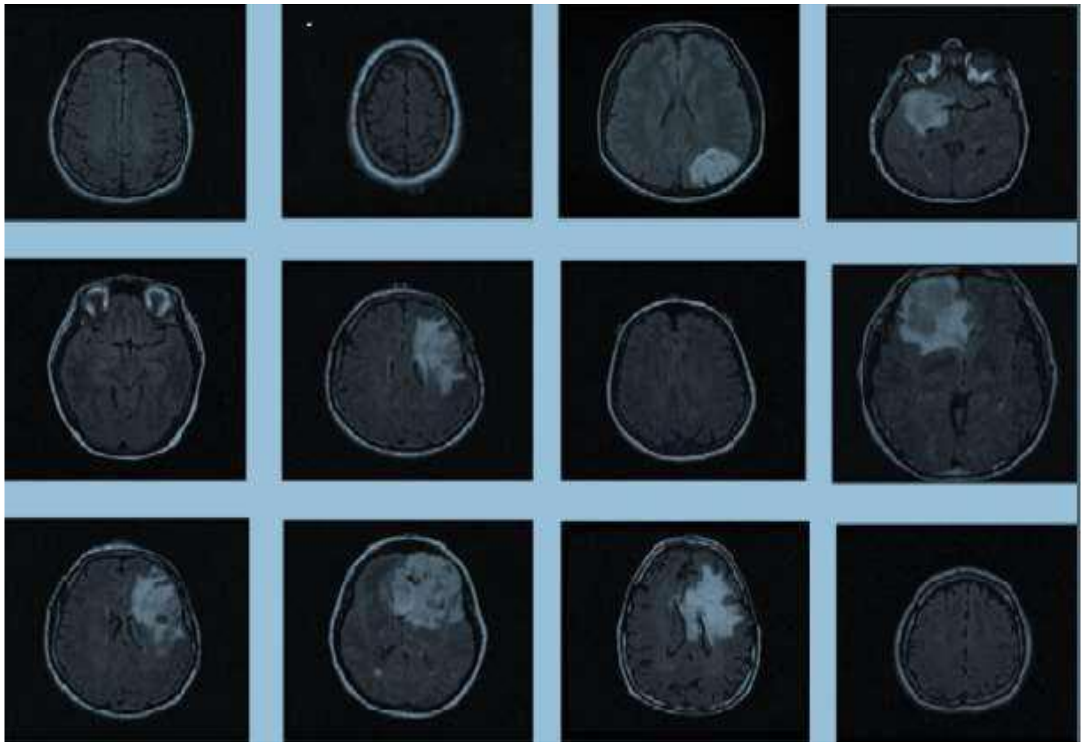

Fig. 1 Examples of brain tumor MRI images with different grades from datastore

This paper proposes to create three fully automatic CNN models using MRI images for brain tumor multi classification. Important hyper-parameters of the CNN models are automatically tuned by grid search optimization. The first of these CNN models is used to detect the brain tumor; hence, it decides whether a given MRI image of a patient has a tumor or not. This task is called Classification-1 throughout this paper. The proposed CNN model for Classification-1has13 weighted layers (1input, 2convolutions, 2ReLU, 1normalization, 2maxpooling, 2fully connected, 1 dropout, 1 softmax and 1 classification layers) as shown in Fig. 2. Because the first CNN model is designed to classify a given image into 2 classes, the output layer has two neurons. The last fully connected layer, which is a two-dimensional feature vector, is given as an input to softmax classifier, which makes the final prediction whether there is tumor or not. Refer to Table 2for more information about the CNN architecture

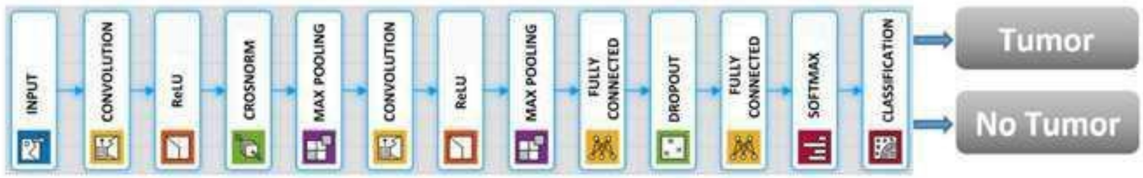

Fig. 2 Architecture of the proposed CNN model for Classification-1 task

Fig. 3 Architecture of the proposed CNN model for Classification-2 task

3.3 Performance Evaluation

It is critical to assess the classification performance of image classification research in order to provide scientific support for the findings of the investigation. Unless this is done, the categorization research will remain unfinished and intellectually unsound. There are a variety of performance evaluation metrics that 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 utilised 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. Eq. 1 shows the corresponding for-mulas for each of these metrics, as well as 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.

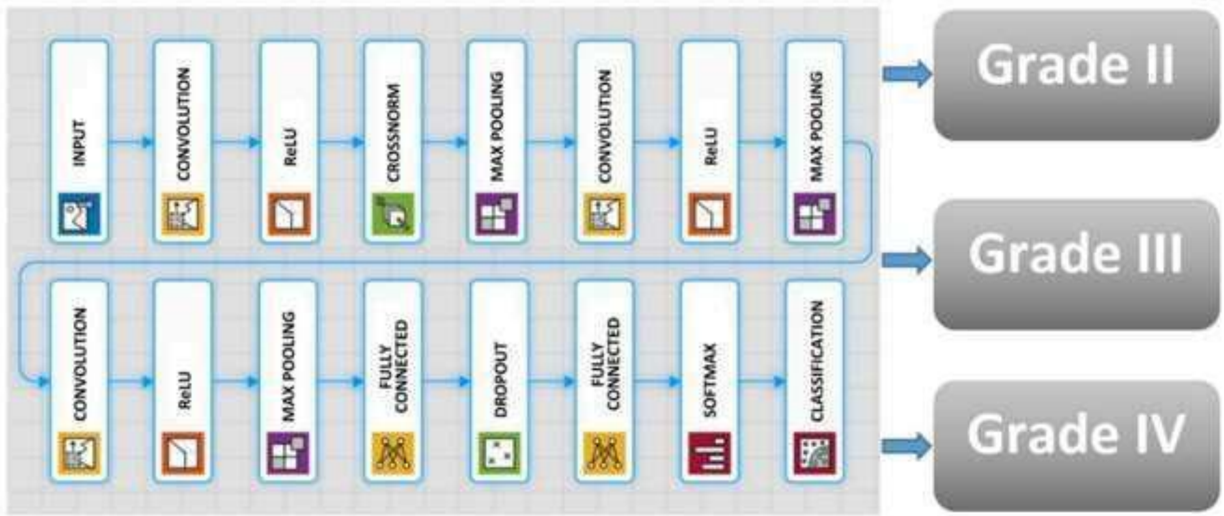

Fig. 4 Architecture of the proposed CNN model for Classification-3 task

4.1 Hyper-Parameter Optimization

There have been some issues in the usage of CNNs in the area of medical image processing as a result of the rising use of CNNs in this discipline. 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 as well as accomplishment of more successful outcomes are largely dependent on the usage of powerful hardware. As a result, the grid search optimization approach is used to automatically tune practically all of the critical hyper-parameters of the proposed CNN models, which saves 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 methods. 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. 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 regularisation, momentum, mini-batch size, and learning rate, to name a few examples.

4.2 Results obtained by optimized CNN models

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 in order to obtain the average classification performance of the model 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. 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 tumour patients). Table 8 shows the picture distribution for 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 utilised for testing reasons only.

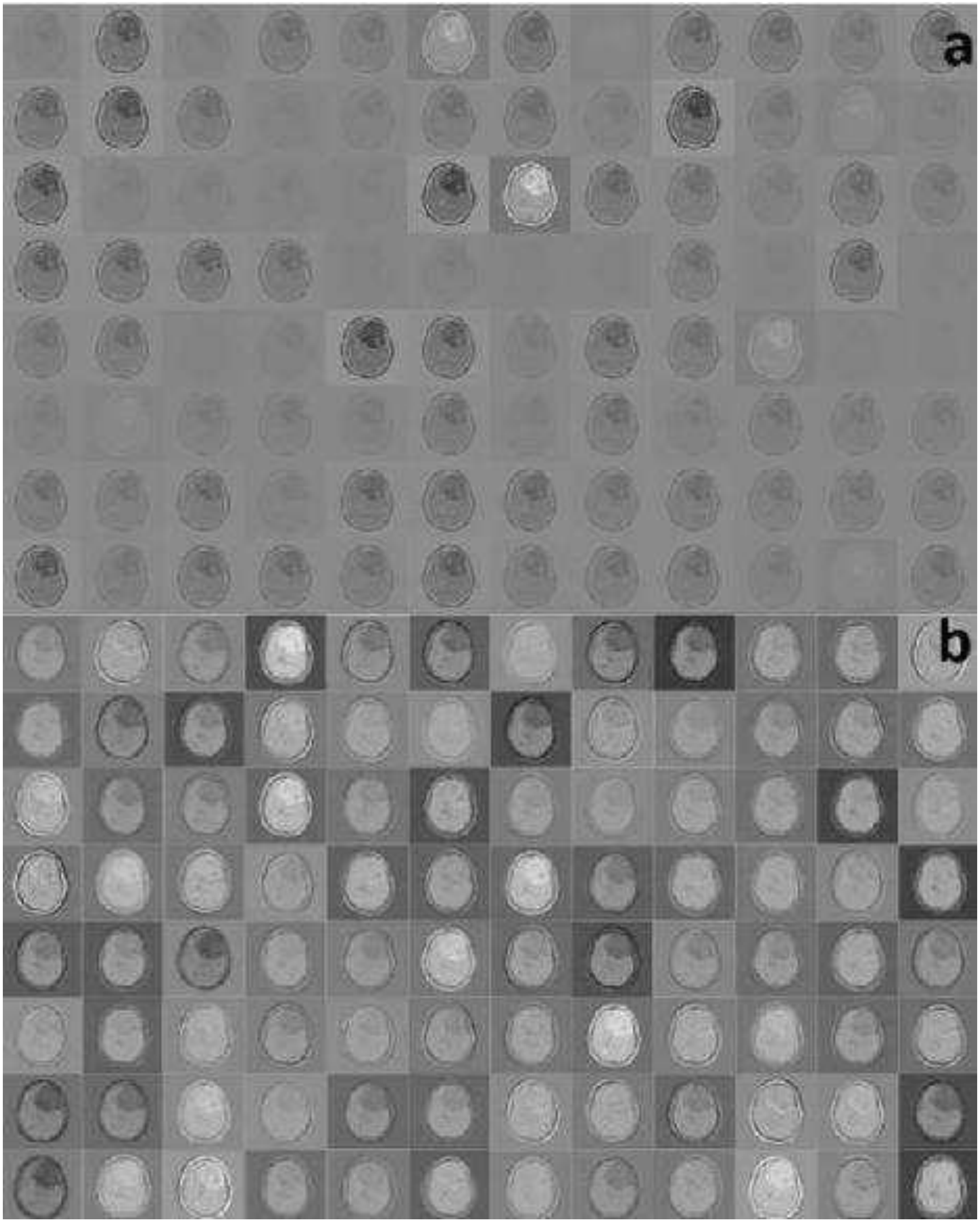

Fig. 5 First a and second b convolutional layer activations for Classification-1 task. Each image in the grid is the output of each channel. White regions show strong positive activations, whereas gray sections show not-strongly activated channels

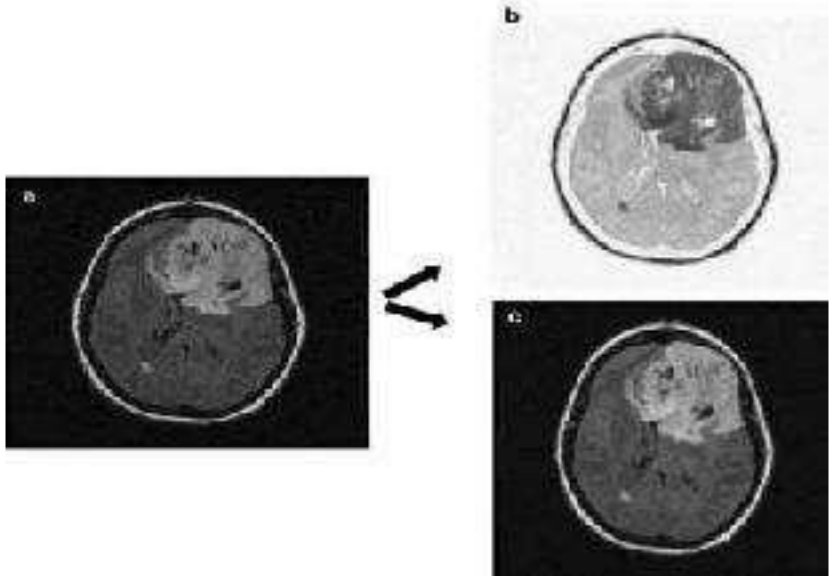

Fig. 6 a Input image, b activations in a specific channel and c the strongest activation channel of the first convolutional layer for Classification-1 task. White pixels in c show strong activations which shows that this channel is strongly activated at tumor position

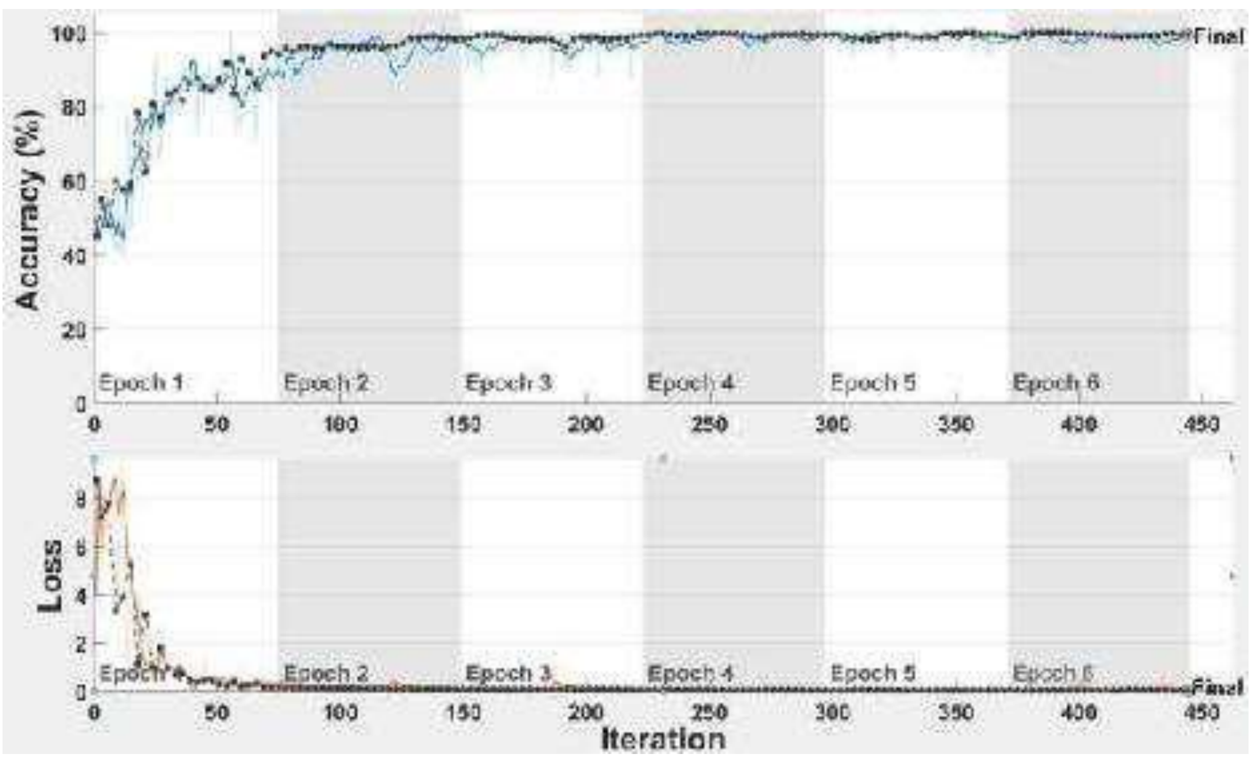

Fig. 7 Accuracy and loss curves for Classification-1 task

5 Discussions

In recent years, image categorization using convolutional neural networks has become more popular in the identification of medical disorders. It is neither conceivable or reasonable to develop an efficient CNN model that can be used in conjunction with other classification models to get excellent results across the board. This is why each issue type has its own CNN model, which is created specifically for it. Depending on the kind of issue, the inputs, and the predicted outputs, the CNN model's structure and complexity may differ significantly. In this work, three separate CNN models are developed for three different categorization goals, each with its own set of parameters. The first model is intended to identify brain tumours using MRI pictures provided as input. The second model is intended to determine the kind of brain tumour, and the third model is intended to forecast the grade of the brain tumour, 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. A good outcome, particularly in convolutional neural networks, is heavily reliant on selecting the appropriate hyper-parameters (or optimization parameters). It is proposed in this work to utilise a grid search optimizer to create the most successful CNN model and to optimise 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 tumours with a 99.33 percent accuracy, which is really good in this case.

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