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Brain Tumor Image Prediction from MR Images Using CNN Based Deep Learning Networks

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Abstract

Finding a brain tumor yourself by a human in this day and age by looking through a large quantity of magnetic-resonance-imaging (MRI) images is a procedure that is both exceedingly time consuming and prone to error. It may prevent the patient from receiving the appropriate medical therapy. Again, due to the large number of image datasets involved, completing this work may take a significant amount of time. Because of the striking visual similarity that exists between normal tissue and the cells that comprise brain tumors, the process of segmenting tumour regions can be a challenging endeavor. Therefore, it is absolutely necessary to have a system of automatic tumor detection that is extremely accurate. In this paper, we implement a system for automatically detecting and segmenting brain tumors in 2D MRI scans using a convolutional-neural-network (CNN), classical classifiers, and deep-learning (DL). In order to adequately train the algorithm, we have gathered a broad range of MRI pictures featuring a variety of tumour sizes, locations, forms, and image intensities. This research has been double-checked using the support-vector-machine (SVM) classifier and several different activation approaches (softmax, RMSProp, sigmoid). Since "Python" is a quick and efficient programming language, we use "TensorFlow" and "Keras" to develop our proposed solution. In the course of our work, CNN was able to achieve an accuracy of 99.83%, which is superior to the result that has been attained up until this point. Our CNN-based model will assist medical professionals in accurately detecting brain tumors in MRI scans, which will result in a significant rise in the rate at which patients are treated.

Keywords: Brain tumour, Magnetic Resonance Images (MRI), Deep Learning, CNN, SVM, Image reorganization

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Introduction

The brain is an important organ that is made up of nerve cells and the various supporting tissues that surround and protect them. Any injury to these subcomponents of the brain is irrevocable and can lead to critical disorders such as brain tumors in the future (Kibriya et al., 2022). Research shows that brain tumors are among the main causes of death around the world. Recent reports have indicated that there has been a discernible upsurge in the number of cases of brain tumors in India. The unchecked proliferation of cells in the brain is the primary cause of this condition. In the case that these aberrant cells are not discovered during the early phases of their development, they will eventually collect in one area of the brain, which will lead to functional changes in the brain (Soomro et al., (2022). Benign tumors (tumors that do not cause cancer) and malignant tumors (tumors that cause cancer) are the two primary categories that these growths fall into, according to the severity level of the condition. 85-95% of these patients report for brain tumors, which are the most common type of primary cancerous tumour. In addition to this, almost 3,460 kids below the age of 12 were given a diagnosis of brain tumor. It was also claimed that every year there are approximately 28000 new instances of brain tumor and that 24000 deaths are reported owing to brain tumor (Patil et al., 2023).

A great number of researchers were encouraged to build various segmentation and classification algorithms as a result of these data, which concerned them. Nevertheless, there is a significant demand for strong algorithms that may detect brain tumors earlier and more accurately in their earlier stages (Rao et al., 2023). Imaging techniques and MRI have only become available in recent years as a result of advances in medical technology. These techniques allow for a more accurate examination of the brain. In particular, MRI of a patient is easier to access and offers improved information for diagnosing brain tumors (Senan et al., 2022). The MR images of the brain, both normal and pathological, are depicted in figure 1. The absence of a tumor is depicted in Figure 1(a), and an aberrant MR picture caused by a brain tumor is shown in Figure 1(b). Not only do the dimensions of these tumors shift from image to image, but their shapes and locations also change. However, they also have less contrast in comparison to the places that are nearby. As a consequence of this, manually identifying these tumors is a process that is both time-consuming and prone to errors, which might lead an experienced physician to treat the patient incorrectly.

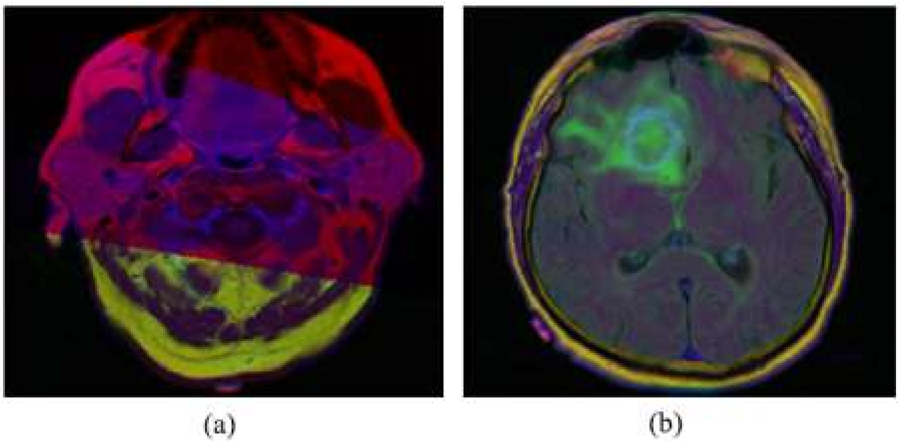

Figure 1. MR-images (a) no tumour (b) affected by tumour

The human brain is, in most cases, the most sensitive portion of the individual body. The mass escalation in the brain, as opposed to the growth of these cells in other disorders, leads to a great deal of change in the behavior and properties of the brain. Additionally, it creates a barrier that prevents the brain from functioning properly. This malfunctioning or abnormality is one of the signs that a brain tumor is present. To put it another way, a brain tumor develops when cells in the brain grow out of control, which results in the formation of the tumor (Ramana et al., 2023). It is responsible for around 13% of all deaths around the world and causes cancer, which can be the cause of death in some cases. The severity of the danger posed by a brain tumor is estimated by a criterion, with the type of tumor, its behavior, size, location, and stage of growth. Cancers of the brain and other nervous system organs were responsible for the majority of human deaths (Baskar et al., 2023). It ranks as the tenth most general reason of death among both men &women. According to estimates regarding brain tumors, "it is estimated that 23,890 adults in the United States (13,590 men and 10,300 women) will be clinical tested in the current year with primary cancer of the brain and spinal cord."

These numbers are based on estimates of the number of people who have brain tumors. In addition, it is anticipated that 18,020 adults would died in 2020 as a effect of primary malignant brain and CNS tumors. There are primarily 2categories of brain tumors, which are benign &malignant. Benign-tumors are those that do not include malignant cells and cause less harm to humans than other types of tumors. Malignant tumors, on the other hand, are characterized by the presence of cancerous cells that provide a greater threat to human health. This can only be done once the tumor has been clinically suspected of being a brain tumor. On the basis of this information, it is simple to make a determination regarding the patient's appropriate treatment, which may include radiation therapy, chemotherapy, the most effective therapy, or surgery (Lokesh et al., 2022).

According to (Sampath et al., 2023), the most important factor is that the proper discovery of the brain-tumor (BT) at a premature stage can protract the likelihood of endurance of a patient who is infected with the disease. The introduction of several different advanced imaging methods has brought about a significant sea change in the medical industry. According to (Madhavi et al., 2023), these medical imaging approaches can detect complicated disorders in people, such as brain tumors, COVID-19, malignant cells, and cancer of the central-nervous-system (CNS). The MRI approach is becoming increasingly popular as a non-invasive method for detecting anomalies in tissue composition. The magnetic resonance imaging (MRI) technique offers a wealth of information and quality anatomical picture forms for the purpose of identifying clinically suspected diseases. In totaling to this, it is playing an extremely significant part in the field of medicinal and biomedical research.

According to (Sucharitha et al., 2022) the most notable benefits of MR imaging are great spatial decree with cross-section pictures, which are significantly more effective for the diagnosis of soft tissues. However, throughout the investigative process of a patient, CT scans release radiation that might be dangerous. On the other hand, magnetic resonance imaging (MRI) does not expose patients to any radiation and can be performed on patients of all ages and stages, including pregnant women and children. In addition, magnetic resonance imaging

(MRI) is capable of producing accurate visualizations of anatomical structures within the human body, particularly within the brain's soft tissues. In order to generate a cross-sectional image of superior quality, it conducts the examination using radio waves and magnetic fields (Islam Khan et al., 2022).

According to the most recent research, (Chillakuru et al., 2023) in the year 2021, there will be 24530 persons in the USA investigated with malignant-tumors in the brain. Of these, 13840 will be males, and 10690 will be women. There is a less than one percent chance that an individual would get this kind of brain tumor during the course of their lifetime. It is responsible for 85–90% of all primary tumors found in the CNS and the focus of this article is on primary brain tumors in adults. Cancer affecting the brain and other parts of the nervous system ranks as the 10th utmost cause of mortality for people (Sucharitha et al., 2023). As a result, it is necessary to work toward increasing the precision of previously suggested methodologies in order to advance medical imaging study. Our study proposes a CNN-based algorithm with an accuracy of 99.74%, which will assist medical representatives in their treatment jobs without requiring manual analysis of MRI images. This will allow the treatment time to be increased, as illustrated in figure 2.

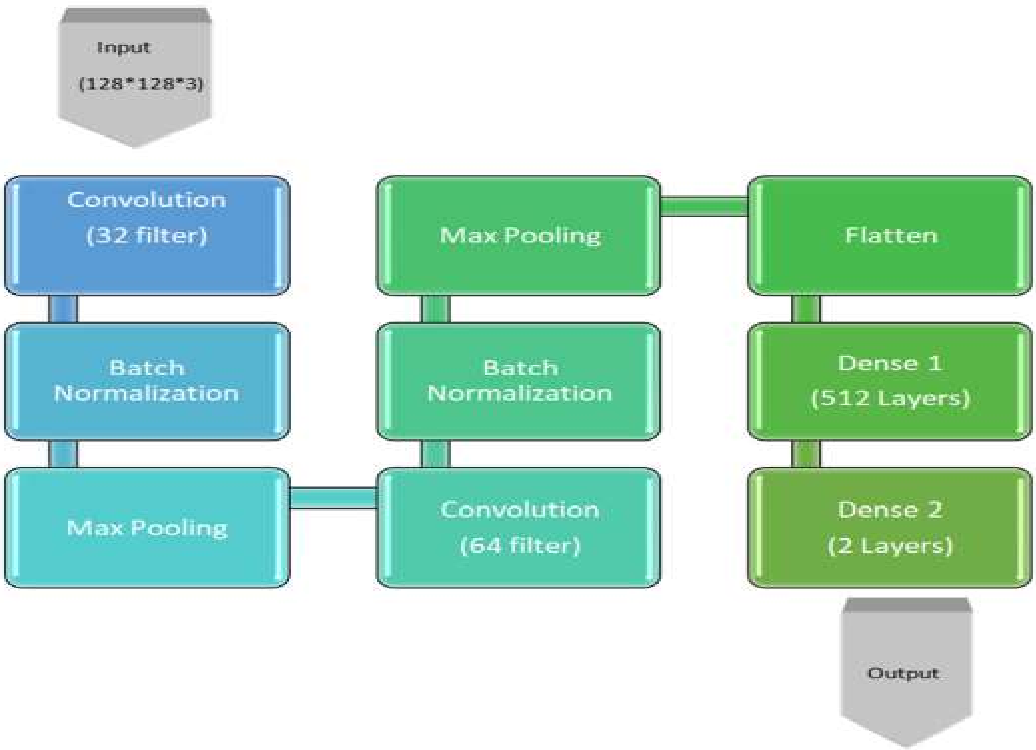

Figure 2. Concept diagram of the proposed Model

The following is a summary of the suggested model's most important contributions:

- To improve the accuracy with which the brain tumor region is segmented from MR images, a unique end-to-end CNN based deep learning is used. This will improve the accuracy of spotting abnormally small tumors.
- Second, it uses SVM and activation learning to extract the most important features (FI) while minimizing the memory allocation issues that plagued earlier algorithms. Improved network performance in segmenting low-contrast tumor regions is the primary goal of these efforts.
- The training parameters have been successfully decreased using the proposed technique. The batch normalization method is used to standardize the extracted characteristics. The network's reliability improves as a outcome of the elimination of average and standard-deviation problems.
- To alleviate overfitting, class imbalance, and other similar issues, the suggested network is trained with a hybrid loss-function, which is achieved by mixing category and binary-cross entropy-functions.
- Finally, the suggested network's performance is measured across a variety of datasets. The output showed that the implemented design is superior to the previous works, with a highest dice coefficient of 99.83% being achieved.

The remaining sections of this work can be summed up as pursues: Section2 illustrates the supplementary materials. In Section3, we present the resources and procedures that make up the implemented detection strategy. Section4 summarizes the outcomes and debates, and Section5 discusses the conclusion and future drawings.

Methodology

In recent years, automated segmentation and classification algorithms have been playing a key part in the process of identifying various illnesses through the examination of the relevant medical images. Implementation of various automated screening devices contributed to the overall improvement of the health care industry brought about by automated techniques (Xie et al., 2022). There are a number of algorithms that can discover diverse pathological things from medical photos by utilizing ML & DL approaches. These algorithms may be found in the published research. Although machine learning systems are able to achieve greater performance, they primarily rely on manually constructed procedures for the extraction of features and the selection of features. In addition, the selection of these features is typically quite complicated and has a detrimental effect on the overall efficiency of the approach. The challenge of feature selection can be alleviated by deep learning techniques along with the correct adjustment of hyperparameters (Maqsood et al., 2022).

An edge detection model was presented in (Shanmugaraja et al., 2023) for the purpose of segmenting cancers from MR images. Despite the fact that this method achieves a similarity index of 0.6407, which places it in a better performance category, it is unable to handle with boisterous images. In (Younis et al., 2022), authors created a finely tuned CNN for the purpose of classifying MR pictures as either normal or tumor images. RBCNet was utilized (Shaker et al., 2023) in order to segment the red blood vessels, and then quicker RCNN was utilized in order to count the blood vessels. Using information regarding brain parcellation (Sathiyamoorthi et al., 2021), built a MI-UNet that is capable of classifying the stages of a brain stroke. In order to increase the performance of U-Net when it comes to extracting nuclei from histology images, they used both residual &inception components. These segmented nuclei will be beneficial in determining the severity of the cancer. By incorporating those components, RIC-UNet was able to achieve nuclei segmentation outcomes that were more accurate through the application of multi-scale characteristics (Rinesh et al., 2022). This approach, on the other hand, was not capable of automatically selecting features from a variety of resolutions. In (Zahoor et al., 2022), authors built an approach in the shape of a bridge that makes use of a cascade process to mine features from the forefront by making use of the Mi-U-Net chunk. This brings the total number of parameters down from 31.03 million to 0.07 million. However, larger clinical datasets cannot be tested successfully using this strategy.

The ability to diagnose a brain tumor from an MR image is becoming increasingly difficult in modern times. Doctors are capable to analyze tumors from MRI of the brain after the patient has undergone surgery or a biopsy to get a tissue sample. In recent decades, a huge quantity of deaths has occurred as a result of erroneous outcome with a larger degree of variability in the diagnosis of brain tumors. Following this, a great range of ML strategies have been developed and applied for the diagnosis of BTs (Kumar et al., 2023). In the medical industry, these strategies are applied with the purpose of reducing the number of manual encounters. "However, these methods were less accurate and required more time to complete (because they were not automated)" As a consequence of this, the manual interaction-based detection might be necessary in order to make up for these deficiencies. This design works by automatically detecting tumor images from mental MR scans and extracting tumoral properties from the scans. However, the aforementioned strategy needed an extra kernel to convolve the feature graph and softmax in order to classify images pixel-wise. The approach only determined whether or not a tumor existed by analyzing MR pictures of the entire tumor region without segmenting it.

In (Stadlbauer et al., 2022), authors have adopted the FD-U-Net in order to get rid of the objects that appear on 2D-PAT images through the process of renovation from sparse-data. Because of these fully dense parts of the network, it is able to reconstruct the data with a greater degree of precision than CNN. Despite the fact that this network has effectively reduced the number of reconstruction mistakes. However, it does not always distinguish between artifacts and vessels, and when it does; it will be liable for the loss of information. NAU-Net was constructed by in (Shelakar et al., 2022) utilizing U-Net++ &attention

components that mine features to rebuild the lunar-bases. This was done to bypass information loss issues like the ones described above. In addition, in order to determine the lunar crater impact, this strategy favors the use of template ML strategies over more traditional image-processing techniques. This design made use of batch-normalization so that it could train very quickly and have an easy time setting the layer weights initially. In (shah et al., 2022), authors (Raza et al., 2022; Seetha et al., 2018) developed an upgraded version of the traditional YOLOv3 that can identify brain tumors using electromagnetic imaging systems. The post-processing of the scattering parameters allows for the reconstruction of the final images that have been collected at the receiver end. Nevertheless, this approach obtained a lower level of validation results (Hossain et al., 2019; Ahmed et al., 2023). In this paper, a novel deep-CNN applied with SVM and activation function is presented for the segmentation of BTs from MRIs. The goal of the paper is to remove all of the drawbacks that are associated with the techniques that have been discussed previously (Suneel et al., 2024).

Experimental Design

In the realm of the medical image processing, the application of a CNN is a method that is highly organized. It is a sort of ANN that is utilized in picture recognition and dispensation. It was developed expressly for the reason of acquiring knowledge of technique components. These activities often involve the utilization of machine vision, which includes picture and video identification, coupled with recommender functions and natural-language-processing (NLP). The functioning of neurons in the human brain is analogous to that of a neural network, which might be a hybrid system consisting of both physical components and program code. The image processing is not the best application for artificial neural networks.

A CNN makes use of a system that is quite similar to that of a multilayer viewpoint but was developed for more efficient process requirements. The removal of constraints and increase in processing power for images results in a system that is far more powerful, and it is much simpler to train it with data for both the image processing and the linguistic communication processes. We revamped the CNN model from the ground up, and the result is a significantly improved version of the original. In 9-layer CNN design, there are a total of 14steps, not counting the hidden-layers, which allow us to achieve the most terrific results possible when it comes to the detection of the tumor. The proposed methodology is depicted as a diagram and is accompanied by a brief explanation in Figure 3. In this experiment, we made advantage of the data from the 2020 BraTS. We obtained a total of 3243 pictures of various tumors, including T1, T2, and FLAIR scans. This dataset is divided into 2classes, with class1 referring to photos of tumors and class 0 referring to pictures of other types of lesions than tumors.

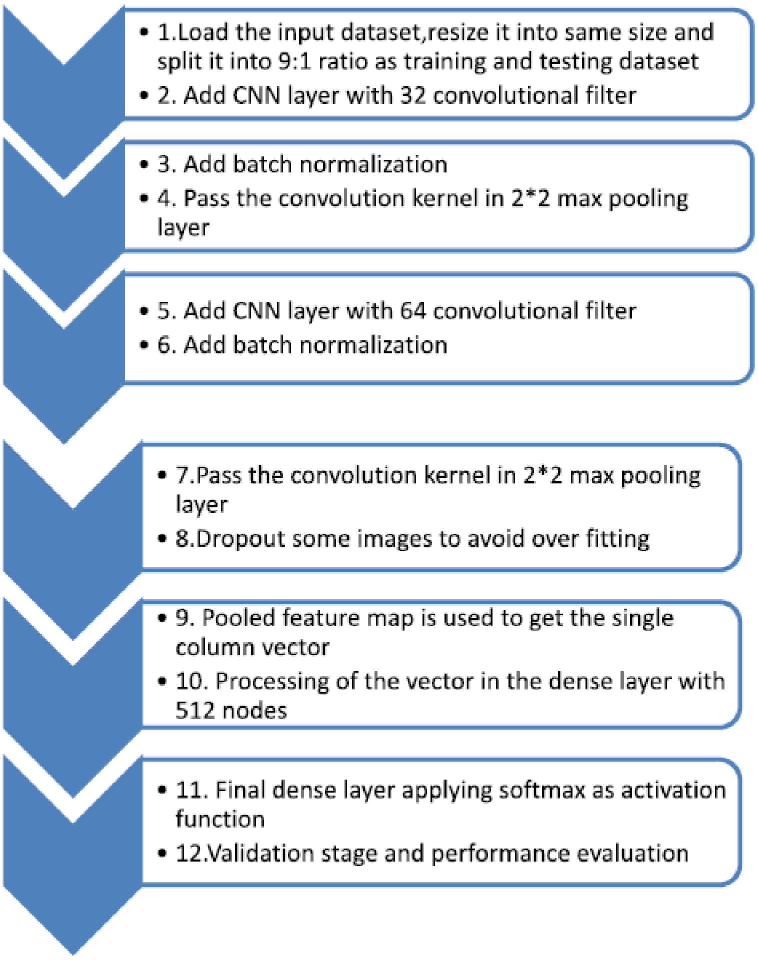

Figure 3. Work flow of the proposed CNN approach

In the method that we have proposed, we have used a wide range of pictures as input, and then we have turned all of the pictures into a single image with the proportions 128×12×3, making their sizes uniform. We have a tendency to generate a convolutional-kernel that is convoluted with the input-layer by ad-ministering 32convolutional filters of size 2×2 each with the assistance of 3channel tensors. Because of the activation function, ReLU is the algorithm that we most frequently use. If the input is negative, the corrected linear activation-function, also identified as ReLU, will produce the value-0 as its result. If the input is positive, however, the function will produce the value-1.

A typical architecture for a CNN consists of stacking numerous convolutional &pooling layers one on top of the other in sequential order. The dimensions of the feature maps can be made more manageable with the use of pooling layers. Thus, fewer parameters are needed to determine the network's computation level. The pooling layer summarizes features in a convolutional layer-generated feature map range. Since the convolutional layer generates correctly positioned features, subsequent operations are performed on summarized data. This helps the model discriminate between feature positions in the input picture. We utilized a 2×2 Maxpooling approach to select the filter's maximum feature map element. It produces a feature-map with the most imperative features from the preceding feature-map, as seen in figure 4.

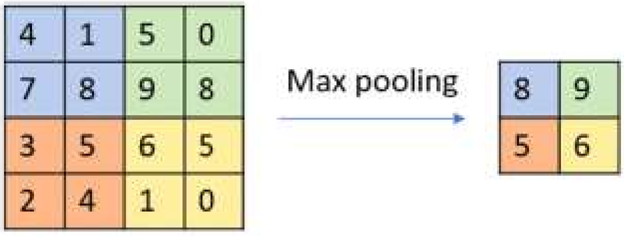

Figure 4. 2×2 Max-pooling function

After completing this stage, we next utilized the 64 filter convolutional, and max-pooling algorithms one more time before flattening the data. We suggested having two thick layers, with the initial dense-layer containing 512hiddenlayers and the second denselayer containing the ending two layers. Because it provides a higher level of accuracy than the alternatives, we decided to utilize the softmax activation-function in the very final layer. We again utilized "categorical_crossentropy" as our lossfunction and RMSProp as our optimizer. RMSProp is an Adaptive Gradient Algorithm modification of gradient-descent that adjusts step-size for all features utilizing a moribund mean of limited gradients.

The photos of brain tumors are classified by CNN as either having a tumor or not having a tumor. The training of CNNs requires an enormous amount of data, yet the image datasets that are currently accessible can only identify so many types of cancers. Because of this constraint, efforts that use CNN to identify brain tumors almost exclusively employ pre-trained CNN models. SVM and activation learning models are utilized in the application of the system. The pre-trained networks' softmax layers are responsible for picture recognition. In order to achieve the best trained system feasible, the system is given repeated opportunities to learn about each of these networks through the use of stochastic gradient descent with momen-tum (SGDM). Although the characteristics obtained from the pre-trained networks with preset parameters can be useful in the classification of tumors, it is possible to train a classifier that is more accurate by fine-tuning the parameters of the network.

Performance metrics

The performance of the implemented design is assessed according to the usual metrics for performance evaluation. Accuracy (Acc), specificity (Sp), sensitivity (Se), and precision (P) are their respective abbreviations. The algorithms for calculating these metrics are provided further down. In addition, performance is judged based on how accurately various classifications are made using a variety of criteria. Among these measurements is the production of a comparison graph for the TruePositive and FalsePositive factors, as well as the counting of TruePositive and FalsePositive factors.

Equation 1 is used to determine accuracy (abbreviated as Acc).

Accuracy (Acc) is calculated by using equation 1

$$\text{Acc} = \frac{Tr_{Positive} + Tr_{Negative}}{Tr_{Positive} + Tr_{Negative} + Fa_{Positive} + Fa_{Negative}} \quad (1)$$

Sensitivity (Se), Specificity (Sp) and Precision (P) are computed using equations (2), (3) & (4) respectively.

$$\text{Se} = \frac{Tr_{Positive}}{Tr_{Positive} + Fa_{Negative}} \quad (2)$$

$$\text{Sp} = \frac{Tr_{Negative}}{Tr_{Negative} + Fa_{Negative}} \quad (3)$$

$$\text{P} = \frac{Tr_{Positive}}{Tr_{Positive} + Fa_{Postive}} \quad (4)$$

Results and Discussion

The findings of our experiments are presented in Tables 1 and 2 and involve a variety of designs, activation-functions, and optimizers of CNN. In a broader sense, this is anenlarge to the GDO approach, and then establish a correctness of 99.83% utilizing softmax in the end-layer & RMSProp as optimizer. This was attained for utilizing 2586 numbers of training pictures and 657 numbers of testing images with a 9:1 splitting ratio. To avoid overfitting, we had to exclude certain photographs from the original dataset of 3243 pictures, which came to about 5 percent of the total. The performance evaluation of proposed activation learning models may be found in Figure 5. Figure 6 depicts the accuracy of the train &validation with regard to the total amount of epochs, and Figure 7 displays the loss that resulted from this accuracy.

Table 1. Performance evaluation of diverse techniques

Activation Function	Optimizer	Acc(%)	Test Acc (%)
SVM		16.28	24.68
Sigmoid	RMSProp	98.27	60.15
Softmax	Adamax	97.92	76.23
Softmax	RMSProp	99.83	92.59

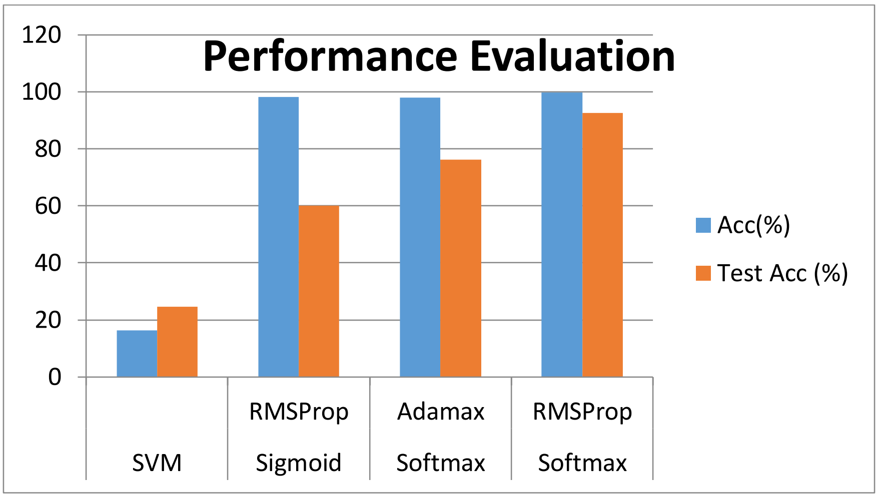

Figure 5. Performance evaluation of Models

Table 2. Accuracy of the Proposed Model with different conditions

Train Images	Test Images	Split criteria	Acc (%)
2586	657	80/20	99.82
2673	323	90/10	99.84

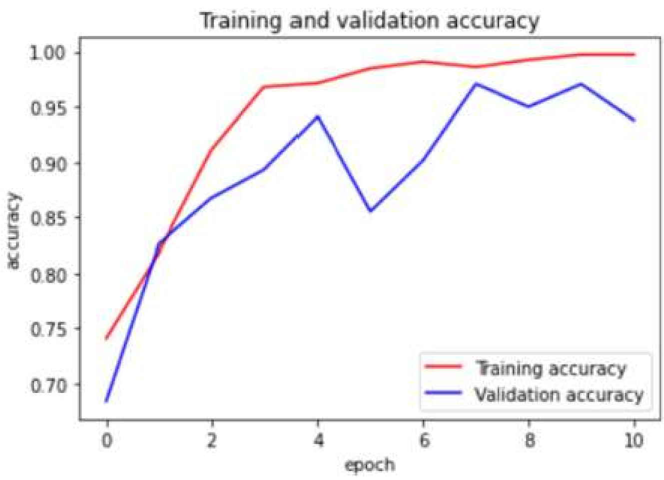

Figure 6. Train &validation accuracy

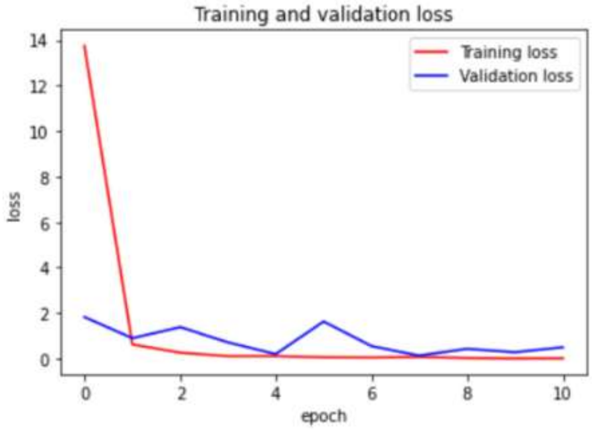

Figure 7. Train & validation loss

In this model that we have suggested, we were able to get an accuracy of 99.84%, which is greater than the findings of the traditional models that were acquired by Seetha et al., and Tonmoy et al., as shown in Table 3. Figure 8 presents a contrast of the efficiency of the executed model with that of formerly published research. Figure 9 displays an example of the expected output image for your convenience.

Table 3. Performance Comparison

Model	Acc (%)
Seetha et al. [27]	96.89
Tonmoy H et al. [28]	97.12
Proposed approach	99.84

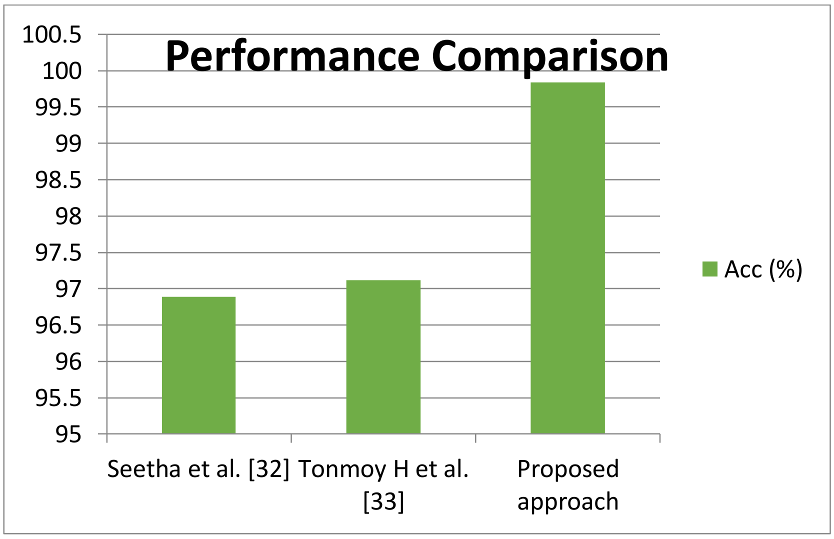

Figure 8. Performance comparison with existing works

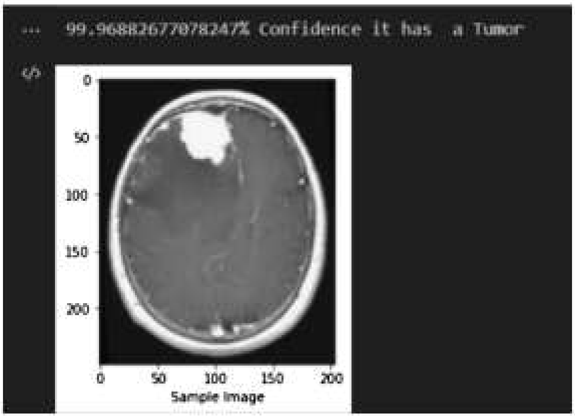

Figure 9. Sample output of proposed CNN model

Conclusion

The main universal application of MRI is for the segmentation and classification of tumors. We decided to improve CNN's accuracy despite the fact that it has the gain of mechanically learning diplomat intricate features for both healthy-brain and malignant tissues via multi-modal MRI scan. Initially, attempted to use SVM on CNN, but the results were disappointing, with an accuracy of only 20.83%. After that, we experimented with a variety of parameters. We modified the last layer's parameters by switching the optimizer to AdaMax and setting softmax as the layer's parameter. After that, we acquired an accuracy of 98.10%. However, as we require more, we chose to switch the optimizer to RMSProp. After some trial and error, we were finally successful in increasing the output accuracy to 99.84%. We eventually arrived at our conclusion by employing a process that involved 11 iterations and a 9:1 ratio amid the quantity of training photos (3243) and the quantity of test images (323). The structure of our model consists of a 9-layer CNN model with 14 phases. The removal of some photos was another crucial step we took to address the issue of overfitting. This research has only been validated for the use of standard datasets. This approach will be further developed and evaluated based on real-time conditions in further research.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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