Brain Tumor Classification using Deep Learning Methods

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ABSTRACT
Brain tumor is a destructive and most prevailing disease that leads to the death of life. Thus, treatment planning is a crucial task that could enhance the quality of a patient's life. There are various image techniques like computed tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasound imaging that are employed to measure the tumor size in the lungs, brain, liver etc. Classification of Tumor and non-tumor can be done, but it has some limitations, like only a limited number of images can be measured accurately and quantitatively. Therefore, an automatic classification scheme plays an essential role in preventing the death rate of human beings, rendering us a challenging task. For this purpose, we take some MRI images to classify tumors by examining the massive amount of data generated by MRI scans. This work proposes an idea in which the Convolutional Neural Network (CNN) is deployed for the classification of tumors. a deeper convolution layer is designed to improve the performance by using a small kernel size. Surgeons and radiologists can classify brain tumors more efficiently and effectively using this technique. Extended CNN achieves approximately 99% accuracy rate by showing the experimental results onward.

Keywords: Tumor, Magnetic Resonance Imaging (MRI), Tumor Classification, Convolutional Neural Network (CNN).

1. INTRODUCTION

In the computer age, neural networks and deep learning have influenced machine learning, with representation learning techniques that allow a machine to create unique representations from raw data. The reason behind the popularity is the hierarchical and layered structure of the network. The idea of CNNs is taken from the human visual system and learns features through an object's compositional hierarchy, beginning with simple edges and progressing to more complicated forms. A convolutional and pooling layer stack achieves this. Each convolutional layer finds the applicable state of being joined together to make the attribute more prominent than the preceding layer of the similar features by downsizing the feature map. Deep learning has also stimulated neuroscience researchers, and they have started to find the solutions for the problems associated with neuro-imaging. Deep Learning has attracted much attention to solving problems in various sectors, including media picture analysis. This study offers an extended deep learning (CNN)-based pipeline for the detection of brain tumor illness and stages using magnetic resonance imaging (MRI) data. In Palestine, cancer is the second major death cause and could also become the prime death cause in the several decades [1].

The detection and the treatment at early stages are the most effective ways that lead to limitize the deaths caused by cancer. The rapid advancement of image processing and soft computing technologies has substantially boosted the interpretation of medical images and contributed to the next step. However, detecting, analyzing, and treating cancer has become a large analysis field. Modern imaging technology is before a specified delivery producing on our quality of detecting cancer at the early stage of strictly sickness correctly dialectically. By contrast, on the other hand, the potency and exactness identifying and treating the image process technologically, has been widely implied to observe and recognize cancer, by its analysis dialectically and effectively to make its statement for cancer in future.

A tumor is the uncontrolled growth of brain tissues at intervals because any tumor is the cause of inherently severe and critical sickness [2]. One hundred and twenty variants of brain tumors have been identified so far. They will be malignant or nonmalignant (benign), and in either case, will be even dangerous to life. Brain tumors are categorized on the basis of their cause and the behavior of the tumor cells. Brain Tumor could be of first or second stage. The category of brain tumor is classified using the size of the tumor. Most physicians use the WHO's organization to spot the form of tumor. Brain tumors, meningioma, nonmalignant pituitary tumors, and nerve sheath tumors are

considered as the primary brain tumors. Brain tumors are graded based on their malignancy level, as illustrated in Figure 1. Grade (I) in the top row indicates that cell growth appears to be typical and expected. Cells are growing slowly. Grade (II) at the second row of Figure 1 is evil. It is spotted that cells show changes from their traditional look. The third row of Figure 1 Grade (III) growth of cells is different from the previous grades. In this section, cells are growing speedily, and the shape of cells is different from the traditional look. In the Last section, grade (IV) Shows that the growth of cells is abnormal in look.

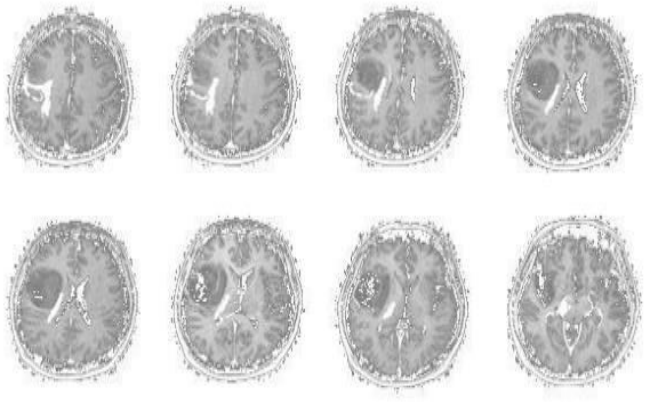


Figure 1: Brain Tumor Images

2. LITERATURE REVIEW

Most researchers are interested in detecting neoplasm cells using imaging images [3]. Throughout this part, we have presented several recent and related efforts to detect neoplasm cells within a given brain imaging image. Chandra et al. proposed a PSO-based primary approach for detecting tumors from imaging images. This algorithmic rule determines the centroids of a range of clusters. Each cluster teams along tumor patterns derived from human images predicted that image segmentation and detection of neoplastic objects would have relied primarily on fuzzy C [4]. The neoplasm objects in the resonance (MR) brain images are traced using a color-based segmentation technique that employs the k-means agglomeration technique [5]. The ost plan behind color-based segmentation algorithmic rule with K-means is principally to convert a given gray-level man image into a color area image then separate the position of neoplasm objects from alternative things of associate man image by victimization K means agglomeration and histogram-clustering. The author uses a FUZZY C-MEANS algorithmic rule for image segmentation and to discover the neoplasm objects within the human image [6], introduced parallel fuzzy c suggests that algorithmic rule for tumor segmentation on multiple imaging pictures primarily connected with the big datasets. So, to attenuate the time for segmentation and the area needed, a gray level bar chart is employed by FCM. Also, the projected technique looks to be doubly quicker than the standard FCM. Next, Tumor detection and segmentation are accomplished using bar chart thresholding and the Artificial Neural Network approach [7, 8].

This approach proposes a modified Artificial Neural Network (ANN) model that relies on learning vector quantization with image and knowledge analysis; the modification intends to carry out automatic tumor categorization victimization imaging - scans. To evaluate the performance of this modified ANN, the classification accuracies and process time live are used. Then, in [9], a region-expanding algorithmic rule with an automatically seeded purpose is projected to identify brain cancers. The work primarily focuses on automatic detection of brain tumors and segmentation that offers anatomical structures and probable aberrant tissue to explain surgical decisions. This segmentation of brain tumors suitably could be a difficult task in imaging. Because the tumor is in its early stages, the edges are not crisp, so the segmentation results are incorrect. Thus a different approach is used in which the detection and the segmentation of the tumor line are used to segregate the regular and irregular tissues that leads to the identification of uninvolved and involved space, allowing MD to precisely differentiate the involved space. The strategy proposed here is a seeded region growing method for determining tumor boundaries in second imaging for various scenarios.

The author intended to develop an automatic segmentation system for detecting brain tumors [10]. The author used patient images of polymorphous brain tumors in this case. Once the preprocessing and elimination of regions with no valid data is complete, they generate a projection image for determining the tumor's initial location. This image depicts the tumor as a whole. The first section can then grow to phase the entire tumor. A hybrid strategy for brain

tumor victimization SVM and the genetic algorithmic program was planned. The use of the medical image process has been exaggerated, particularly for medical applications. This increases the qualified radiologist's variety of agencies navigating, viewing, analyzing, segmenting, and interpreting medical pictures [11]. The analysis and visualization of the medical image received from the acquisition devices appreciate PET, CT, or imaging area units formidable to gauge thanks to clinical knowledge. Therefore, the amount of noise in medical pictures is thanks to the scanners. Computerized analysis and automatic data systems facilitate handling significant amounts of knowledge, and new image process techniques might facilitate de-noise those pictures.

3. BACKGROUND

A brain tumor is defined as an aggregation of abnormal cells that are enclosed by the human skull. Any type of unusual cell development presents a concern. The tumors of the human brain could be malignant (cancerous) or benign (not cancerous) (Non-cancerous). With the growth of a tumor, whether malignant or benign, the pressure inside the skull might rise. This pressure can harm the brain and cause a person to die. The brain tumor could be categorized as of primary or secondary nature. The brain tumor of the primary nature is named as benign and the metastatic brain tumor is the word used for the tumor of secondary nature, it occurs when the cancerous cells travel to the other parts of the human body. Annually 11000 people are diagnosed with a brain tumor of the primary nature and as far as the UK is concerned, 29 persons are diagnosed daily. It is crucial to note that various disorders can present similar signs or symptoms to brain tumors; however, it is critical to recognize them to consult the doctor in severe conditions. There are two kinds of brain tumors, which are addressed more below:

a. Primary Brain Tumor

Such types of tumors originate from the brain, they can develop from brain cells, from the membranes surrounding the brain and the glands and the nerve cells. They could be of benign or malignant nature. In adults, gliomas and meningioma's are very common.

- Gliomas are tumors that are composed of glial cells. Such cells generally sustain the structure of the central nervous system, provide nutrition to it, clear cellular waste, and degrade dead neurons.
- Meningioma is more prevalent in women than in men. This tumor usually is harmless, but it can create difficulties because of its size and location. This type of tumor is scarce but very aggressive.

b. Secondary Brain Tumor

The majority of brain cancers are secondary brain tumors. They begin in one section of the body and metastasize to the brain. The diseases due to metastasize of the brain are given in the following:

- Lung Cancer
- Kidney Cancer
- Breast Cancer
- Skin Cancer

The brain tumors which are of secondary nature are often cancerous, however the benign tumors stay static (don't travel to other parts of the body.

4. BRAIN TUMOR DIAGNOSES

Diagnosis is a fundamental but essential step because it defines the structure of brain tumors and helps the patient and doctor deal with this type of state. Doctors use different types of tests to diagnose brain tumors. Some of the tests are listed below:

- MRI
- Tissue sampling/biopsy/surgical removal of a tumor
- CT scan
- Positron emission tomography (PET) or PET-CT scan
- Neurological, Vision, and hearing tests

There are many tests that doctors advise different patients according to their symptoms, but in this research study, our focus is on MRI and CT scan tests. Here are some brain tumor images given in Figure 2.

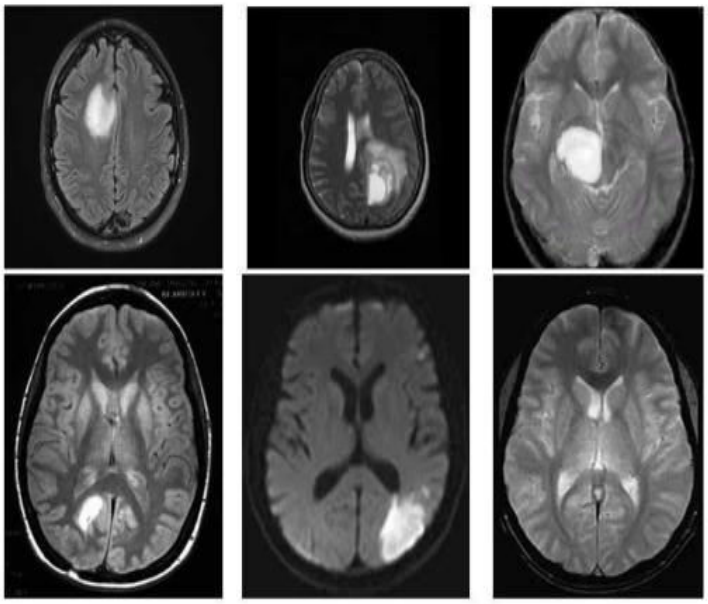


Figure 2: Brain Tumor Images

a. Magnetic Resonance Imaging

In MRI the magnetic field is employed to make detailed images of the human body. The MRI technology could be applied to various body parts on the basis of tumor suspect areas like spinal cord or brain or both. MRI is one of the most effective technologies presently employed for identification of tumors; it uses a robust magnetic flux, radiofrequency signals, and laptop for provision of the in depth photos of soft tissues and body organs. Tomography is most popular due to its better-off than X-radiation scan for designation [12]. Tomography is very easy for the head section because tomography needs focused and motionless objects. However, for the rest of the body because humans need to breathe.

Therefore, to scan the rest of the body, there is minimal time near about 20 sec; during the scanning process, the patient needs to hold his breath for 20 sec, which is very difficult for old age persons or for the person who is already suffering some disease. Compared with MRI or CT, MRI is the latest and fastest solution for detecting tumors and other infected parts of the body. Furthermore, it has no aspect effects on the shape because it does not use any radiation that supports the magnetic flux and radio waves. Conjointly, it provides higher results than MRI because it distinguishes the different soft tissues of the body [13].

b. CT scan

Use the X-Ray to produce 3-dimensional images of the human body. These images are combined into a cross-sectional view showing abnormalities or tumors using a computer. The significant difference between CT scan and MRIs is that CT scan uses X-rays and MRIs uses magnetic fields. Noninvasive imaging modalities such as magnetic resonance imaging (MRI), computed tomography, and positron emission tomography (PET) could be used to diagnose a brain tumor, avoiding unnecessary surgery. Because it gives improved soft-tissue contrast and high-resolution information, MRI is an intriguing method for the anatomical characterization of brain malignancies. Although the approach is still commonly used in clinical practice, it does not detect metabolic alterations. These noninvasive instruments provide in vivo medical imaging and chemical information about tissues, but in vivo application on living animals or humans is prohibited [13, 14].

Medical pictures (including MRI) square measure powerfully deteriorated by noise in the main due to knowledge acquisition systems, numerous sources of interference, operator performance, and alternative phenomena that affect the menstruation processes in imaging which may cause serious classification inaccuracies. Doctors and radiologists' visual interpretation of tumors by doctors and radiologists may be a tedious and fatiguing method, particularly once an extensive range of medical aid units want continuous observation. This method typically needs a simple microscope and may end up in a wholly different and inaccurate designation; however, once handled, This is frequently unacceptable in human existence. The importance of high precision systems, power-assisted systems, and diagnosis systems (CADx) is emphasized. The CADx technology is in high demand in medical facilities because it

may help radiologists and doctors make decisions by delivering a laptop result as a second opinion. As a result, designing a highly automated and cost-effective diagnosis system may be the most significant and gorgeous decoration task. Typically, such a dialectic system is ready to rule in consecutive specific achievement of further choice and classification. Figure 3 depicts the difference between Machine learning and deep learning.

- **Feature Extraction** This step is accountable for extracting all possible options in medical image magnetic resonance imaging that are expected to identify neoplasm while not regarding the shortcomings of unnecessary spatiality.
- **Feature Selection** This step is answerable for tumbling the spatial property by excluding immaterial or unwaged options and checking out the most effective vital options to escape the curse of the spatial property while also reducing computing complexity.
- **Classification** problem happens once a picture must be allotted into a predefined cluster or category supported by various determining options. Image can give precise information regarding an event or a particular object. Image classification techniques like CNN and SVM are the ways to predict that information using an image dataset.

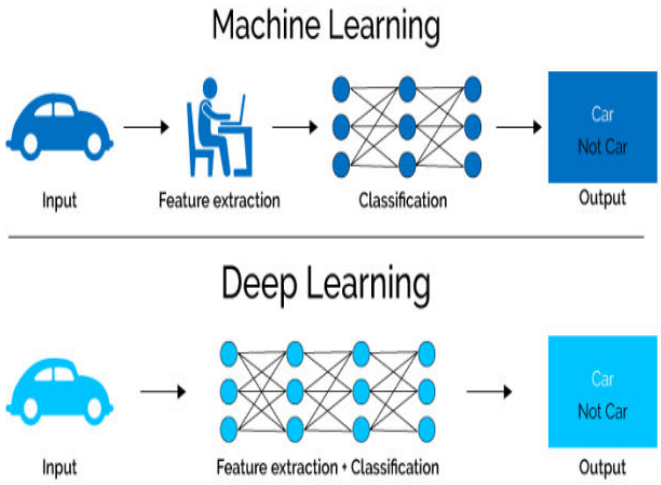


Figure 3: Difference between Machine Learning and Deep Learning

5. BASIC CONCEPTS OF CNN

a. Convolutional Neural Networks (CNNs)

CNN's related to feeding neural network as sign flowed to the specific network as formal loops might be contained, which might be stated as [15].

$$F(x) = f_N\left(f_{N-1}\left(f_1 \ldots\ldots\ldots (f_1(x))\right)\right) \quad \ldots\ldots\ldots\ldots\ldots (1)$$

Here f_N relates to the count of hidden layers and it also shows the activity within the corresponding layer. The most useful layers embrace the convolutional, activation, Pooling, absolutely connected, and declaration layers during a typical CNN model. Within the convolutional layer, f consists of multiple convolution kernels (g_1 ..... g_{k-1}, g^k). Every g^k represents a linear perform within the k-*th* kernel, which might be delineated as follows:

$$\square^{\square}(\square, \square) = \sum_{\square=-\square}^{\square} \quad \sum_{\square=-\square}^{\square} \quad \sum_{\square=-\square}^{\square} \quad \square_{\square}(\square, \square, \square)\square(\square - \square, \ \square - \square, \square - \square) \ldots\ldots\ldots\ldots (2)$$

(x,y,z) relate to the position of pel in input I , W_k is the burden for the k-*th* kernel m, n, and w represents the filter's peak, width, and depth. Within the activation layer, f could be a pixel-wise non-linear operation, i.e. corrected long measure (ReLU) [16].

$$f(x) = \max(0, x) \ldots\ldots\ldots\ldots\ldots (3)$$

In the pooling layer, f could be a layer-wise non-linear down-sampling operation aiming to reduce the scale of the feature illustration. A connected layer is considered a convolutional layer whose convolutional kernel has the scale of one × one. The declaration layer, i.e., Softmax, is superimposed to the immediate past under normal conditions. They are being joined in a close association layer to reason Ii's chances "This student somehow does not belong" to different categories. An associate example of one pipeline CNN model is shown in Figure 4. It Has convolutional

layers, ReLU activating agent, max-pooling, and connected layers. A ReLU activation layer follows each convolutional layer. The first, ordinal and fifth activation layers are followed by a max-pooling layer severally. When the last max-pooling layer, three connected layers follow:

b. Pooling Layer

Spatial Pooling reduces the spatiality of every feature map and, at a similar time, retains the foremost necessary info. Abstraction Pooling may be of various types: easy lay, average, sum. A pooling performance replaces the output of Infobahn at an exact location with an outline datum of the close outputs. Once doing easy lay Pooling, we tend to outline an abstraction neighborhood and take the large-scale component from the feature map of the given window. Rather than taking the most significant component, we tend to conjointly take the typical or total of all parts in this window. The performance of the layer is to cut back abstraction input size illustration increasingly. To be additional actual, Pooling:

- It makes the representations of input smaller and additional manageable.
- Eliminating the extra parameters and calculations within the network to reduce the size of computation increases the efficiency.
- It makes the network more realistic to perform minor transformations, distortions, and translations within the input image.
- It helps us make a virtual scale-invariant illustration of the image, also called equivariantly.
- This layer is compelling because it can detect objects within an image on where they are located.
- One of the main disadvantages of Pooling is losing output spatial resolution.

c. Fully Convolutional Network (FCN)

The significant distinction between FCNs and CNN's lies in FCNs replacing the connected layer with up-sampling and de-convolutional layers [16]. Up-sampling and de-convolutional layers are thought of as a backwards version of Pooling and convolutional layers, and each square measure is learnable. Rather than generating one chance score for every category to classify the total Image, FCNs form a score map with the precise size because of the input image for every category and classify every element of the image. Additionally, FCNs mix the results of earlier layers through up-sampling and deconvolution results of the last layer (also referred to as skip connection) to improve the declaration accuracy. Because of the flexibility of pixel-wise classification, FCNs are mainly adopted for image segmentation. The concept of up-sampling, deconvolution, and skip association inspires deep learning algorithms' events in several applications [17]. Figure 4 shows a pair of associate degree examples of an easy FCN model.

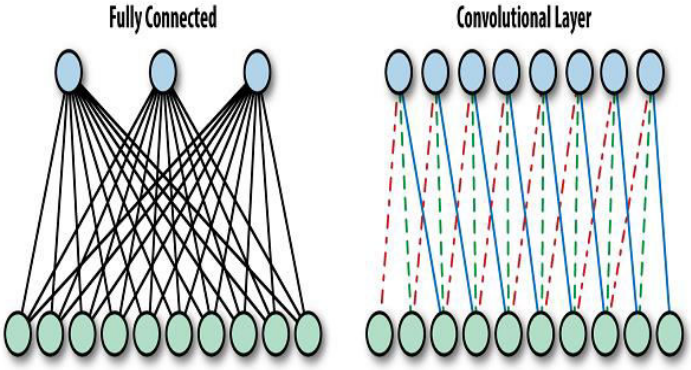


Figure 4: Fully Connected Layer Architecture

MRI is a noninvasive medical test that helps physicians diagnose and treat medical conditions. It is determined that automatic segmentation methodology exploitation Convolutional Neural Network (CNN) with 3*3 kernels give deeper design and positive results against overfitting [18]. The Watershed segmentation formula removes the salt and pepper noise with heavy edges. It is simple for automatic and correct calculation of tumor space. Object detection is a process to identify the object from an image or sequence video (shown in Figure 5). It is still a challenge for computer vision systems. The quality of being at hand when needed as an automatic tool and goal intends to attain human information by leading to reliability and effectiveness for an abnormal new mass of tissue that serves no purpose to observe the treatment [19]. A computed assisted relationship method convinces MRI, and fusion of MRI is promoted and used for diagnosis.

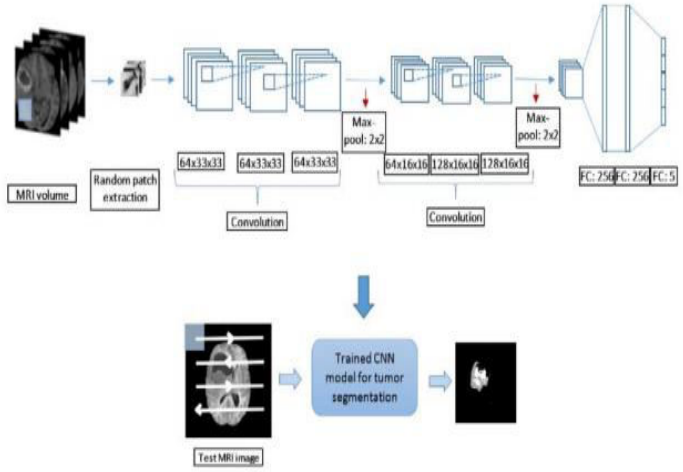


Figure 5: Brain Tumor Classification and segmentation using CNN

6. METHODOLOGY

Cancer is the most harmful illness, detected by one in all the procedures of Magnetic Resonance Imaging. Machine learning with an image classifier may be accustomed to efficiently noticing cancer cells in the brain through magnetic resonance imaging, which saves radiologists and surgeons valuable time. This research work utilizes Tensor Flow to classify brain cancer exploitation of magnetic resonance imaging. In Tensor Flow, we enforce a convolutional neural network with eight layers. Here a total of 1202 magnetic resonance imaging was employed in the dataset out of 600 cancerous and remaining non-cancerous. The coaching accuracy was ninety-nine, and validation accuracy was 99% in fifteen epochs. This method continues to be in development. The system may be used as a second call by surgeons and radiologists to notice tumors efficiently. MRI may be accustomed to notice brain cancer by analyzing magnetic resonance imaging; however, this procedure is time overwhelming for an extensive range of cases. The literature survey we tend to do led the United Kingdom to utilize a convolutional neural network classifier, and we enforced this by exploiting Tensor Flow.

a. TensorFlow

TensorFlow is an open-source library developed by google in 2015 for python language. The purpose of the TensorFlow library is to make the development of algorithms in python language easier and used to train and build deep networks [20, 21]. TensorFlow is designed as an internal library by Google, and developers use it to build in-house models. TensorFlow is derived from multidimensional arrays of neural networks known as 'tensors.' In June 2016, Dean stated that there are 1500 fountains of TensorFlow on GitHub, but there are only five from google. Although several options are available, developers prefer TensorFlow because of its efficiency and ease of use. It is also easy to modify because it is an open-source library. As we discussed before, TensorFlow is used as a python library, and it allows developers to express their results in graphs, bars, and data flow diagrams. Nodes of graphs represent mathematical operations. Data is represented by edges which show the communication of data from node to node information, defining TensorFlow as tensors that are four-dimensional arrays. TensorFlow uses the integrated dataflow graph to represent the procedure of the algorithm and the state on which the algorithm is operated. Vertices represent functional procedures on unchallengeable data in traditional graphs, but TensorFlow allows vertices to represent computations that can update the fluctuating data or state. TensorFlow gives variability to programmers due to its flexible architecture. It provides a way for the programmer to perform different experiments with different parallel schemes. Each edge contains multidimensional arrays between nodes. To provide more transparency to TensorFlow over more than 150-year, Google uses TensorFlow and then releases it as open-source for all users.

b. Theano

Python is a universal language. Theano is a library of python programming languages that deal with mathematical expressions and optimizes these expressions for better results. Theano is primarily working on multidimensional arrays like NumPy Array. Theano provides the facility to deal with large amounts of data without changing the CPU. The user composes the expressions in high-level description Theano understands the factor and converts these expressions is C++ for CPU (CUDA for GPU), which makes it more convenient. Theano compiles

them automatically and loads them into dynamic modules of python language [21]; as we discussed earlier that Python is a powerful and versatile language. Python has the flexibility to deal with significant mathematical expressions. However, there is no such powerful compiler or interpreter designed to deal with such complex expressions. Python uses complete objects while the user is expressing only a simple calculation. Therefore, we use the Numpy array to manage these complex expressions in python language. A single Python object can store the large-scale expression using a multidimensional array-like (ndarray). Numpy is used with Python for scientific calculations.

Numpy provides a compelling n-dimensional array. Numpy facilitates the user to perform a very complex operation of the data type, reshaping complex objects, and it is helpful for mathematical expressions. These functions are designed in C language and then integrated into Python to better the results. Many NumPy functions perform very slowly because they are based on the use of memory, in other words, based on the transformation of memory instead of the performance of calculations. The primary functionality of NumPy is ndarray (N-dimensional array). numexpr is also used for numeric data and converts the large-scale data into multidimensional arrays. Still, numexpr uses the strings to encode the data within the code. Numexpr optimized the syntax on a minimal note while writing the code [22, 23].

On the other hand, Theano represents mathematical expressions using Numpy syntax. Access to the graph of full associated expressions leads or provides the advanced features for the symbolic representation of complex expressions; it allows theano to work on the local graph to precise the unnecessary, unstable expressions or patterns. Once graphs are optimized, these graphs can be used in many programs without any changes for implementations of both CPU and GPU. Theano and SymPy are both the same; both libraries manipulate symbolic mathematical graphs, but Sympy deals with a set of more complex mathematical operations of the modern computational system. Theano focuses on the quick and economic analysis of primarily array-valued expressions [24].

7. IMPLEMENTATION

a. Dataset Acquisition

To acquire the dataset from the machine learning repository of UCI, Kaggle Challenges, Figure 3 shares the most prominent positions which provide the dataset that is of slightest vitality. Still, the most important source was BraTS Challenge 2015-16 [25]. Figshare provides the dataset for brain tumor detection. Dataset is based on 3064 images of different patients having tumors. Each image/data is in a .mat file in the dataset, and each file contains five attributes.

- Patient ID
- Label of Image
- Original Image or matrix of Image
- MASK of Tumor
- Border of Tumor

The dataset contains 1320 NIfTI (Neuroimaging Informatics Technology Initiative) images. MRIcron software is used to get the informative images from these files and convert these files into jpeg/png. Proposed work has taken brain images in 3 different positions to get better results and increase the machine's efficiency (shown in Figure 6).



Figure 6: Different Positions of Brain

b. Model Creation

The convolutional neural design used here is elementary lenet architecture. This design contains six layers; out of that, a pair of layers square measure convolutional layer, the opposite a pair of layers square measure pooling layer, and the last layer is connecting layer. In the above layer, the filter size is 2, the number of filters is 32 and 64, respectively, and the fully connected layer contains 1024 sizes of the filter. We use the Tflearn, a high-level API of TensorFlow, which provides an efficient neural network. It helps us create fully connected and convolutional layers adding activation functions and applying dropout regularization.

c. Convolutional Neural Networks

This method applies a series of filters to the raw picture, extracting the feature and facilitating classifying the object (shown in Figure 7). The model contains three components:

- Convolutional Layer The first layer is the Convolutional layer in which we apply a specified number of convolution filters to the image. The layer performs mathematical operations on every sub-region and provides a single-valued map. The Convolutional layer applies a ReLU activation function to the output to introduce nonlinearities into the model.

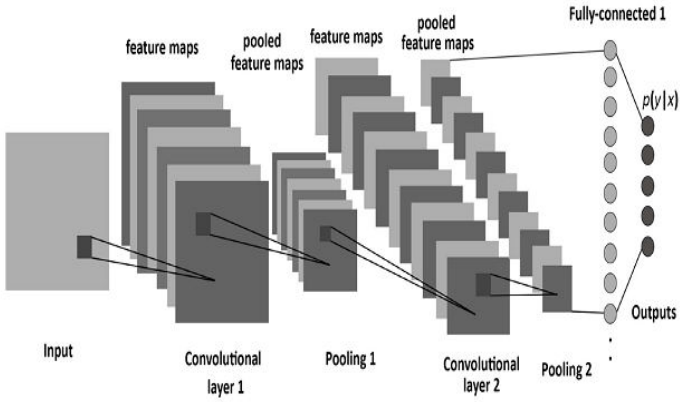


Figure 7: General Architecture of CNN

- Pooling Layer Pooling layers are applied to reduce the output obtained from the convolutional layer. The pooling layer reduces the size of the feature map. Max pooling algorithm is commonly used to extract sub-regions of the feature map (e.g., 2x2-pixel tiles), keeps their maximum value, and discards all other values.
- Fully Connected Layer Fully connected layer is used in the end section. This layer is used to classify the output extracted and downsampled from the above layers. Every node is fully connected with other nodes in a fully connected layer. Usually, a CNN approach is combined in algorithmic stack computation. Each of them is used to perform feature extraction. Every component is based on both the convolutional and pooling layer. Finally, a fully connected layer is used to classify the object. The final layer contains a single node for the target class, with the softmax activation function calculates the values between 0–1 for every node. We convert every image into the array using NumPy and theano. Our model takes it as most data arrays and performs calculations.

d. CNN Architecture

The module is based on the following function to create each of the three-layer types above:

- **conv2d()** This function creates a two-dimensional convolutional layer. As parameters, it accepts the number of filters, the size of the filter kernel, padding, and the activation function.
- **max_pooling2d()** The max-pooling algorithm builds a two-dimensional pooling layer. As parameters, it expects the pooling filter size and stride.
- **Fully connected()** Builds a fully connected layer. As arguments, it accepts the number of neurons and the activation function.

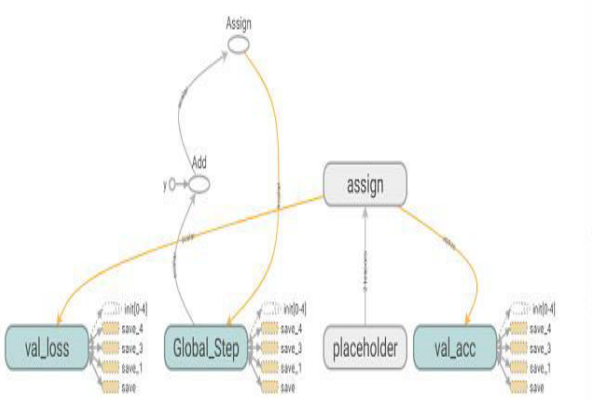


Figure 8: Architecture Graph-1 of the proposed method

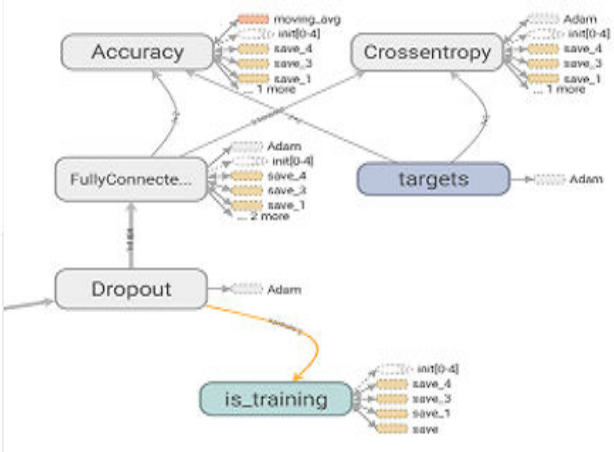


Figure 9: Architecture Graph-2 of the proposed method

The CNN architecture graph created using the methods above is depicted in the diagrams above (Figure 8 and Figure 9). Because the network graph was so large, we divided it into four sections, as indicated in the images. In the proposed method, we use eight layers of CNN. First, the third and fifth layers have filter size 2, and the number of filters is 32 The second, fourth, six, and the eighth layer have filter size 2, and the number of filters is 64. The fully connected layer used by several kernels in CNN is 1024.

Image is converted into matrix form or array of numbers (array) in this architecture. The proposed method first converts the image into 50 x 50 then applies a filter to convert the image into a grayscale image after these conversions. The algorithm applies to the data and produces the results. Grayscale images have less weight as compared to the original image. A fully connected layer takes these batches as input and then combines all these small batches to create valuable information. The Relu layer focused on the highlighted nodes of the images. A fully connected layer combined these nodes and created a feature node to extract information depicted in Figure 10. The main graph of CNN architecture is shown in Figure 11.

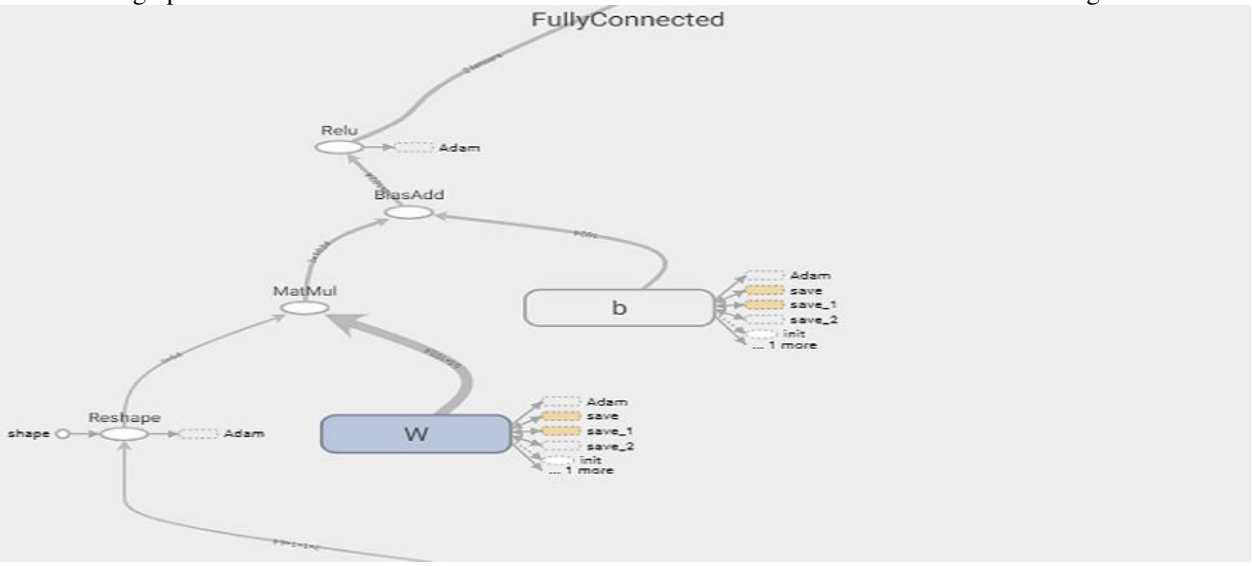


Figure 10: The architecture of Fully Connected Layer

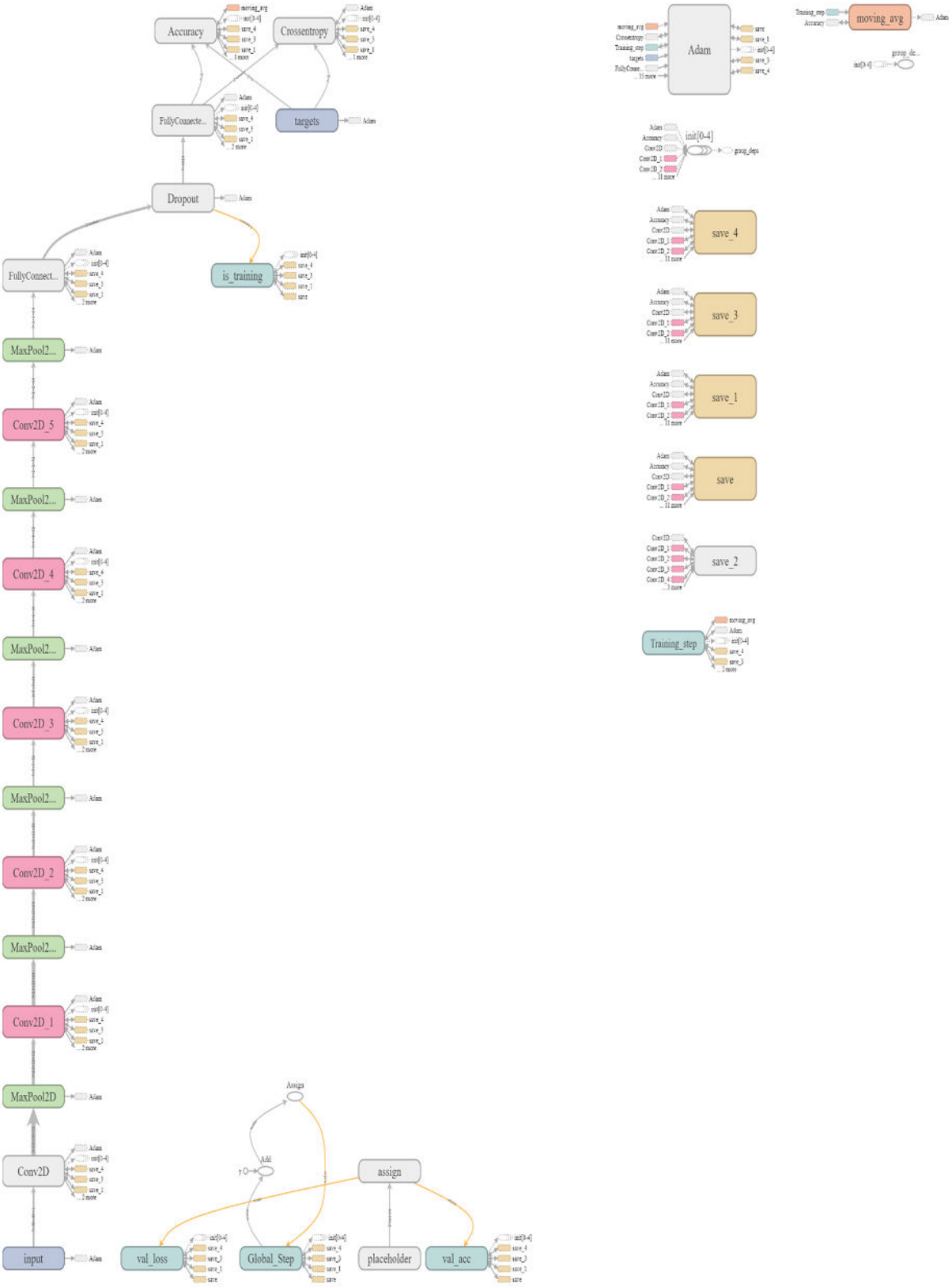


Figure 11: CNN Architecture MAIN Graph-1

e. Epochs, Batch Size, and Iterations

Each epoch represents one forward and backwards pass for all training examples of the network. Several forwarding and backward passes are represented as batch size. Batch size is directly proportional to memory. If the batch size increases, more memory is required. Iterations represent several passes. To be specific, a pass consists of one forward pass and one backward pass. If we had 1200 MRIs in jpg/png format, the memory consumption was more significant than typical, around 6GB. The batch size is sixty, and the number of iterations is 640, resulting in 640 epochs.

8. RESULTS

We try to improve the algorithms using advanced techniques and methods. We have a minimal dataset of MRI images in the proposed work. The dataset contains MRI images of different positions and angles. Proposed research results on a restricted dataset with very high training and validation accuracy are summarized and plotted on a tensor board. The graph curve shown below was produced using 1152 iterations/steps and their respective accuracies. Figure 12 depicts the validation loss and accuracy graph over iterations, which is uneven at first but finally achieves zero as iterations progress0. The loss rate is an important factor in CNN. Improvement of CNN architecture is based on loss rate. Proposed research reduces the loss rate and improves the accuracy using a limited dataset.

```
Training Step: 269  | total loss: 0.08500 | time: 3.532s
| Adam | epoch: 015 | loss: 0.08500 - acc: 0.9944 -- iter: 1088/1152
Training Step: 270  | total loss: 0.07692 | time: 4.751s
| Adam | epoch: 015 | loss: 0.07692 - acc: 0.9949 | val_loss: 0.00333 - val_acc: 1.0000 -- iter: 1152/1152
--
```

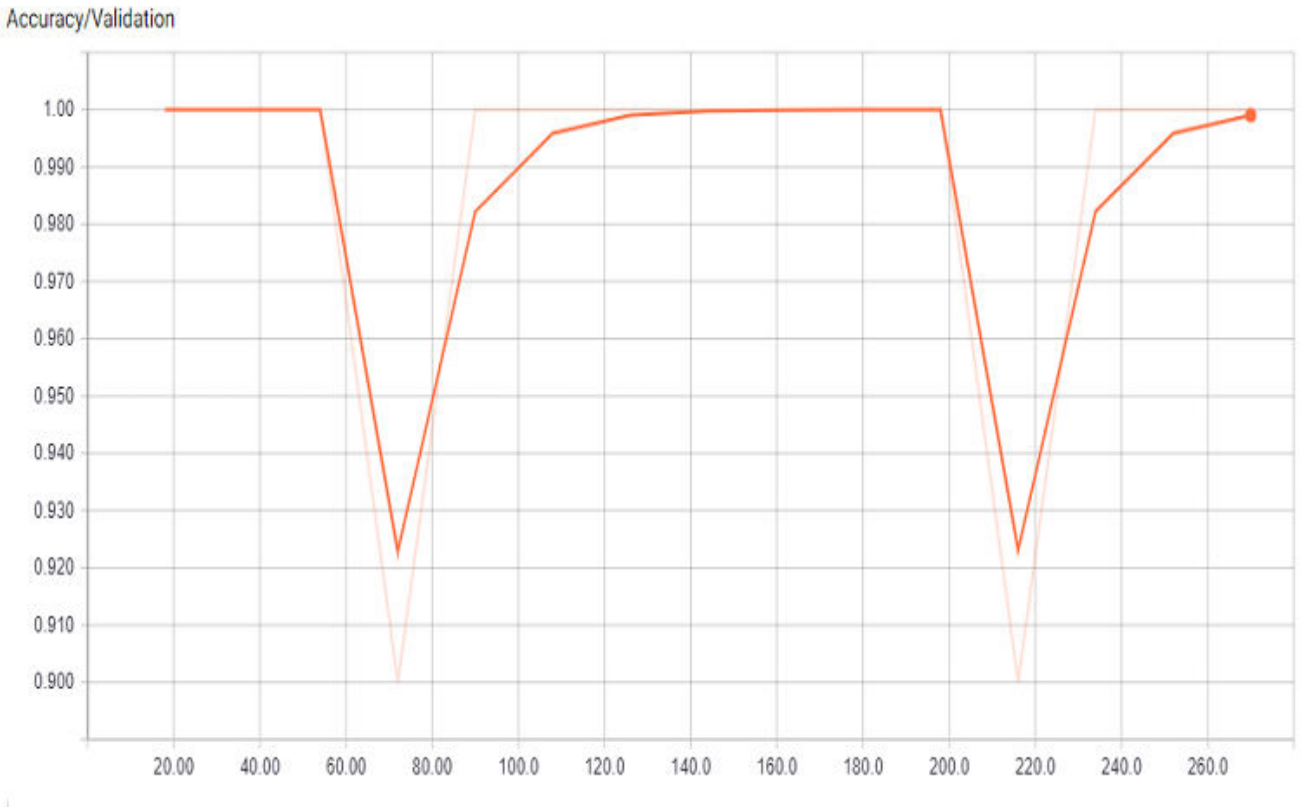


Figure 12: Validation Accuracy Graph

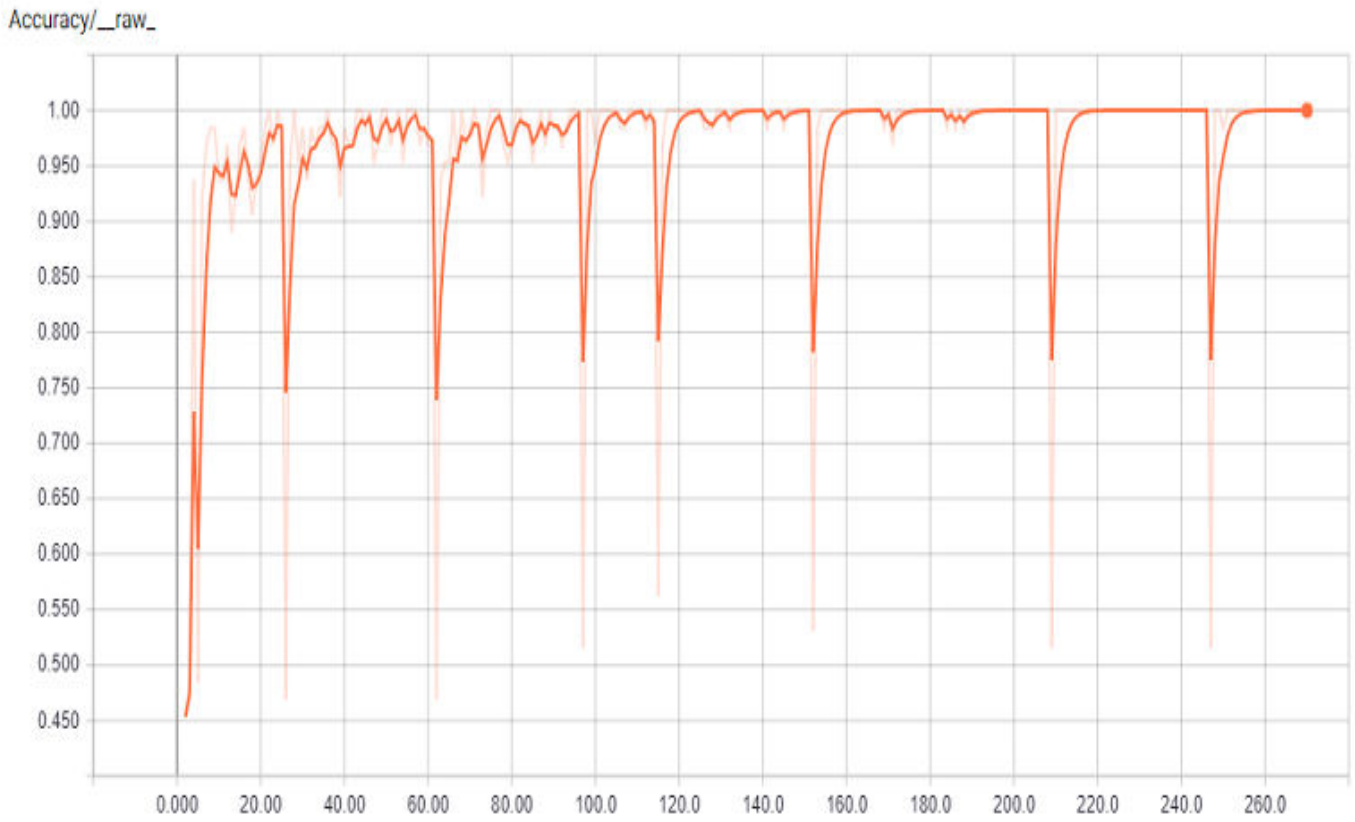


Figure 13: Training Accuracy Graph

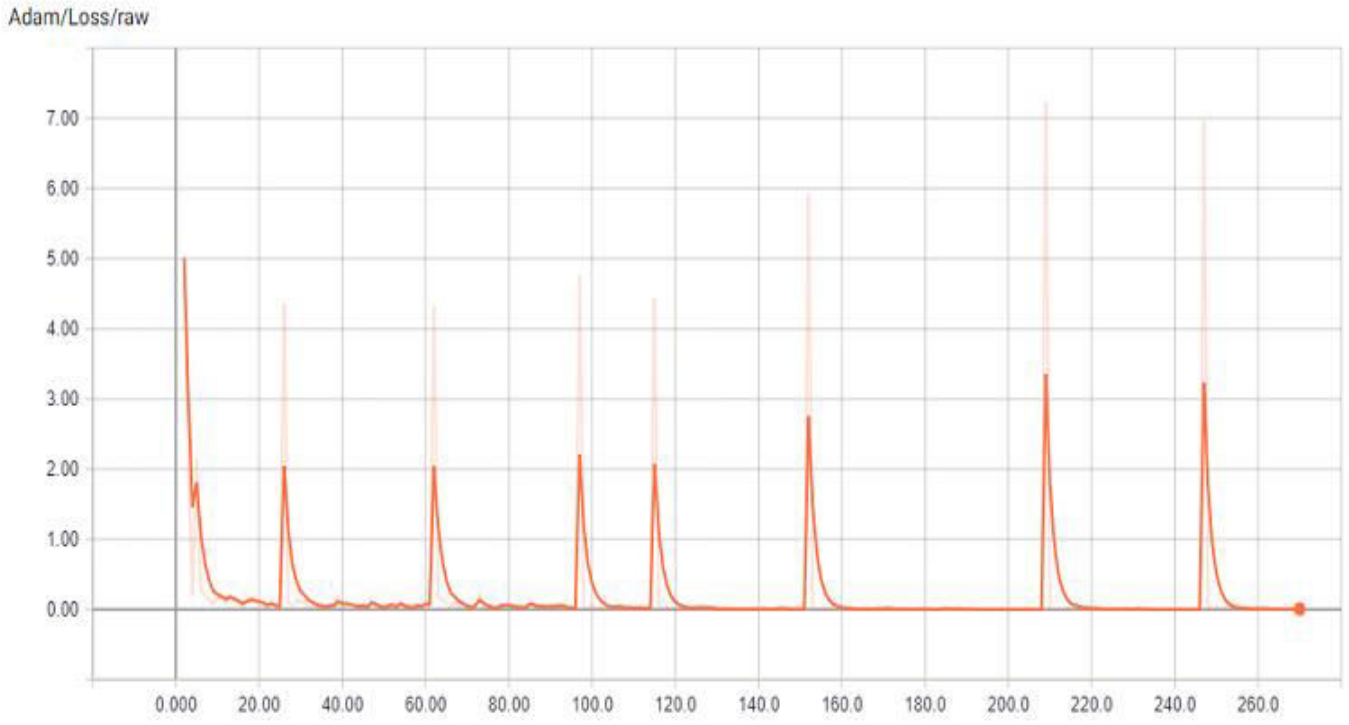


Figure 14: Validation Loss

Figure 13 represents the training accuracy and validation of the proposed method. This accuracy graph shows the learning accuracy of the machine. Figure 14 shows the loss rate, which is 0.00333% and reduces towards 0, which increases the machine's efficiency to predict more precisely.

Table 1: Results

Method	Epochs	Iterations	Dataset	Accuracy Rate	Loss Rate
Proposed Method	15	1152	1202	99.99% Approx.	0.00333%

Above Table 1 shows the accuracy and loss rate of the proposed method. The table shows that the proposed method is more efficient than previous methods because the loss rate is improved. As we already discussed previously, the loss rate and efficiency are inversely proportional to each other. The accuracy rate shows the validation of the algorithm. These figure 15 and figure 16 show the results obtained after applying the method to the image dataset. Results are produced in two forms: the first one is labeled as normal, which shows the non-tumorous part, and the second one is labeled as a tumor, which shows the tumorous portion after classification (shown in Figure 15 and Figure 16 respectively).

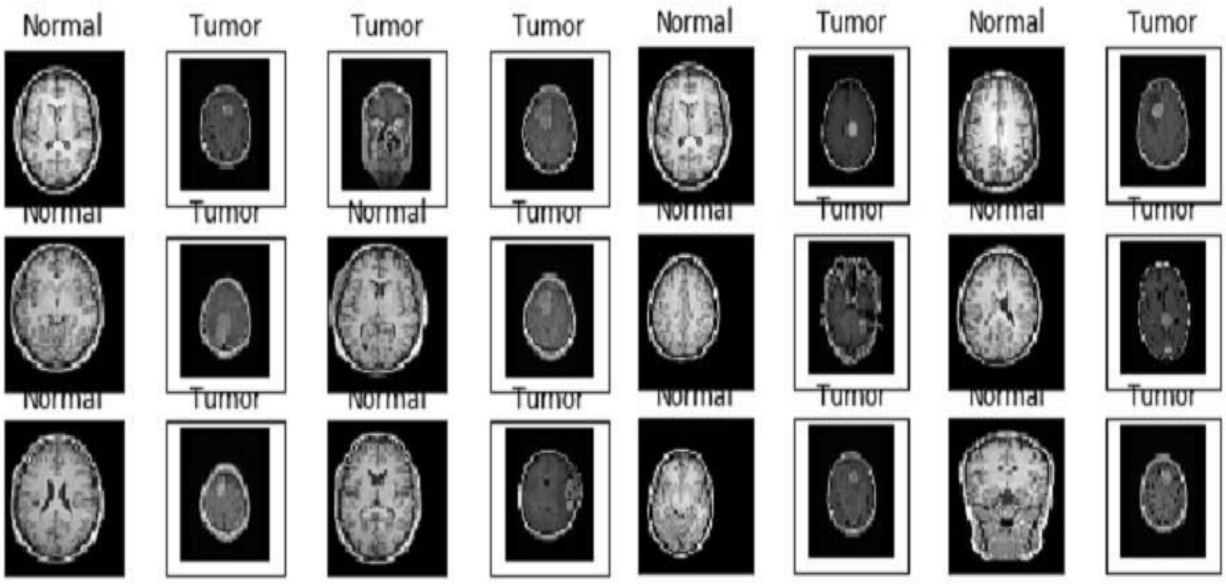


Figure 15: Results -1

Figure 16: Results -2

In the proposed work, we use an extended convolution neural network to enhance the performance using a small kernel and achieve the approximately 99% accuracy rate with the loss rate of 0.0033% leads to 0. Let us compare the proposed method with previous techniques to make it fair. In [26], use the primary convolution network having two convolution layers with activation function like The first two layers are relu and max pool, followed by one hidden layer of 64 neurons. That exhibits a constantly decreasing pattern invalidation loss as the number of epochs grows, resulting in the highest validation accuracy of all five architectures. The best architecture training and validation accuracies are 98.51% and 84.19%, respectively. [26] also attempts to identify brain tumors using MRI and the Convolutional neural network approach. They use basic convolution architecture having five layers: convolutional layer, activation function, max Pooling, and dense layer to achieve high accuracy. The kernel size of the convolution layer is 3, and the total number of kernels is 32,64, respectively. They achieve an accuracy rate of 99% with a loss rate of 0.712. [27] use an intuitive approach capable of reading and categorizing brain MRI pictures as usual or tumor-affected. For region and border identification of brain T2 images, a hybrid segmentation method employing a seeded region growth algorithm is applied. Markov Logic classifies the image to determine the 132 Tumor possibilities. The segmentation is accomplished by a structural strategy, such as a seeded region growth algorithm. By implementing the Markov Logic-based learning ability, the method's performance can be increased. The designed approach's experimental findings outperformed the current approaches by 96.71% for SNR 5DB and

99.96% for SNR 10DB. According to their method, each preceding discussion yields a different classification result. Table 2 shows the comparison between these methods and our proposed methods.

Table 2. Comparison Table of Proposed Method

Method	Accuracy Rate	Loss Rate
CNN [25]	98.51%	
LeNet [26]	99%	0.712%
hybrid segmentation method [27]	96.71%	
XCNN	99%	0.0033%

9. CONCLUSION

The use of computer technologies like computer vision, deep learning, and Image processing helps us in various fields of life like bio-medical and industrial. The use of computer vision and deep learning is very fruitful. After this, it is very easy to classify the brain tumor using MRI images, but many points still need to be improved. We use a deep learning technique like CNN to classify the tumor using limited MRI images in the proposed research. Brain tumor classification is done by analyzing MRI. Machine learning is a compelling strategy for classifying cancer tumors from MRI. We achieved a training accuracy of 99.99% with a validation loss of 0.00333 to 0 over 15 epochs. The method shown in this research study is a fundamental image classification method. The more powerful approaches are available. Our model was created on the CPU-based TensorFlow, and TFlearn, a GPU version of TensorFlow, is much faster to train, resulting in much faster model creation. The more sophisticated system should take MRI images and classify them directly without converting them into grayscales. More advanced techniques like TensorFlow fold can be used in the future. This method makes it simple to create deep learning models that operate on data of diverse sizes and structures.

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