Brain Tumor Detection Using CNN

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Submitted by

Venkata Naga Kalyan Puppala

(AP20110010509)

Under the Guidance of

Dr. Rajiv Senapati

SRM University–AP

Neerukonda, Mangalagiri, Guntur

Andhra Pradesh – 522 240

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Certificate

Date: 14-Dec-22

This is to certify that the work present in this Project entitled "**BRAIN TUMOR DETECTION USING CNN**" has been carried out by **VENKATA NAGA KALYAN PUPPALA** under my/our supervision. The work is genuine, original, and suitable for submission to the SRM University – AP for the award of Bachelor of Technology/Master of Technology in **School of Engineering and Sciences**.

Supervisor

(Signature)

Prof. / Dr. Rajiv Senapati

Asst. Professor,

Department of CSE,

SRM - AP.

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We would like to acknowledge that this project review was completed entirely by us and not by someone else.

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Abstract

Brain tumor is the growth of abnormal cells in brain some of which may leads to cancer. Primary brain tumors occur in around 250,000 people a year globally, making up less than 2% of cancer. In the field of medical image analysis, research on brain tumors is one of the most prominent ones. Tumor segmentation is one the most difficult task in medical image.

The usual method to detect brain tumor is Magnetic Resonance Imaging(MRI) scans. From the MRI images information about the abnormal tissue growth in the brain is identified. In various research papers, the detection of brain tumor is done by applying Machine Learning and Deep Learning algorithms. When these algorithms are applied on the MRI images the prediction of brain tumor is done very fast and a higher accuracy helps in providing the treatment to the patients. These predictions also help's the radiologist in making quick decisions. In the proposed work, a self-defined Convolution Neural Network (CNN) is applied in detecting the presence of brain tumor and their performance is analyzed.

List of Publications

The thesis is mainly based on the results presented in the following articles.

1. Abhishta Bhandari, Jarrad Koppen and Marc Agzarian. 2020. [Convolutional neural networks for brain tumour segmentation].
   https://doi.org/10.1186/s13244-020-00869-4

2. Arkapravo Chattopadhyay, Mausumi Maitra. 2022. [MRI-based brain tumour image detection using CNN based deep learning method].
   https://doi.org/10.1016/j.neuri.2022.100060

3. J. Seetha and S. Selvakumar Raja. 2018. [Brain Tumor Classification Using Convolutional Neural Networks].
   http://dx.doi.org/10.13005/bpj/1511

4. D C Febrianto, I Soesanti , H A Nugroho. 2020. [Convolutional Neural Network for Brain Tumor Detection].
   http://doi.org/10.1088/1757-899X/771/1/012031

Abbreviations

CNN	Convolution Neural Network
MRI	Magnetic Resonance Image
DP	Deep Learning
ML	Machine Learning
ReLU	Rectified Linear Unit
FCM	Fuzzy C-Means Clustering
SVM	Support vector machine
ANN	Artificial Neural Networks
KNN	K-Nearest Neighbour
YOLO	You Only Look Once
CNS	Central Nervous System
CT	Computed Tomography

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1. Introduction

A brain tumor is an abnormal growth or mass of cells in or around your brain. Together, spinal tumors and brain tumors are called central nervous system (CNS) tumors. Brain tumors can be malignant (cancerous) or benign (noncancerous). Some tumors grow quickly, while others are slow growing. Only about one-third of brain tumors are cancerous. But whether they're cancerous or not, brain tumors can impact brain function and your health if they grow large enough to press on surrounding nerves, blood vessels and tissue. In India, 40,000-50,000 people are diagnosed with a brain tumour every year, according to estimates. Out of these, about 20 percent are children.

In the field of diagnosis of cancers and tumors imaging technology plays a vital role. MRI is a non-invasive medical imaging technique that produces detailed images of the inside of the body. It is often used to diagnose and monitor a wide range of medical conditions, including injuries, cancer, and heart disease. Unlike X-rays and CT scans, MRI does not use ionizing radiation, making it a safe and effective imaging method.

Literature Review

1.1 Convolutional Neural Network.

CNN is a type of artificial neural network that is commonly used in image recognition and processing tasks. It is called a convolutional neural network because it uses a mathematical operation called convolution to filter the input data. In a convolutional layer, a filter or kernel is applied to the input data, which is typically an image, in order to detect certain features or patterns in the data. The convolution operation multiplies each element of the filter with the corresponding element of the input data and sums the results, producing a single output value for each position of the filter. This output is called a feature map, and it represents the detected features at each position in the input data.

The convolutional layer is followed by a pooling layer, which is used to reduce the dimensionality of the feature maps. Pooling can be performed in different ways, such as taking the maximum or average value of a group of pixels in the feature map. This step is important because it helps the network learn the most important features of the data and reduce the computational cost of the network.

After the pooling layer, the features are typically flattened into a one-dimensional vector and passed through a fully connected layer, where they are used to make a prediction or classification. This final layer uses the learned features to calculate the output probability for each possible class of the input data.

In summary, CNNs are useful for image recognition tasks because they can learn complicated features from the input data using convolution and pooling operations, and use these features to make predictions or classifications.

1.1.1 Convolution Layer.

In a convolutional neural network (CNN), the convolution layer is responsible for extracting features from the input data. This is done by applying a set of convolution kernels, or filters, to the input data. These filters slide across the input data, performing a dot product between their weights and the input data at each position. This results in a set of feature maps, which are then passed on to the next layer in the network. The weights of the convolution kernels are determined during the training process, using a gradient-based optimization algorithm such as stochastic gradient descent. By training on a large dataset, the convolution kernels learn to extract the most important features from the input data, which can then be used for a variety of tasks such as image classification or object detection.

1.1.2 Subsampling Layer.

Max pooling is a common subsampling method used in convolutional neural networks (CNNs). It helps to reduce the size of the output from the convolution layer, which in turn makes it easier to process in the next layer. By taking the maximum value from each grid, max pooling also helps to increase the invariance of feature positions, meaning that the network can still recognize objects even if they are slightly shifted or rotated in the input image. This is an important property for many image recognition tasks.

1.1.3 Fully Connected Layer.

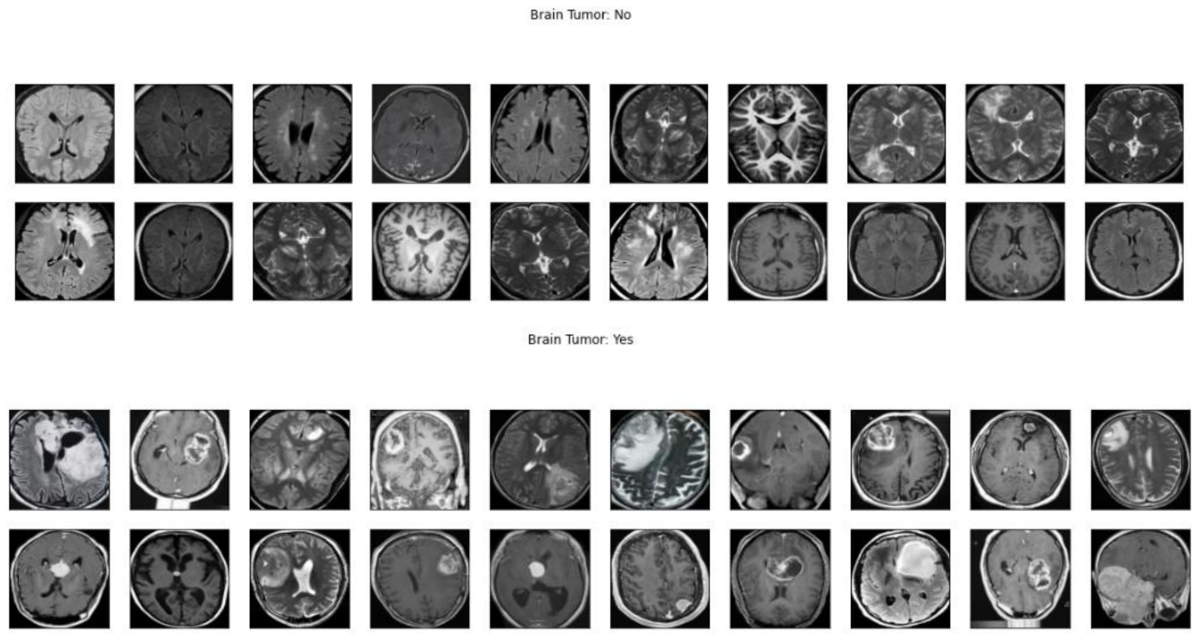
The fully connected layer, also known as the dense layer, is a key component in many neural network architectures. It is used to transform the output of the previous layer into a form that can be used by the next layer. In a fully connected layer, each neuron is connected to every neuron in the previous layer, and the output of each neuron is a weighted sum of the inputs from the previous layer. This allows the network to learn complex relationships between the input data and the output classes. The fully connected layer is often used at the end of a neural network architecture to produce the final output of the network, such as a classification or regression prediction.

2. Methodology

2.1 Dataset.

We have collected the dataset from Kaggle.com as we can't get the MRI scan images directly from a hospital. It consists of 253 samples which are divided into 2 groups, out of which 155 images has tumor in it and remaining 98 images has no tumor.

Figure 1. Sample images of dataset



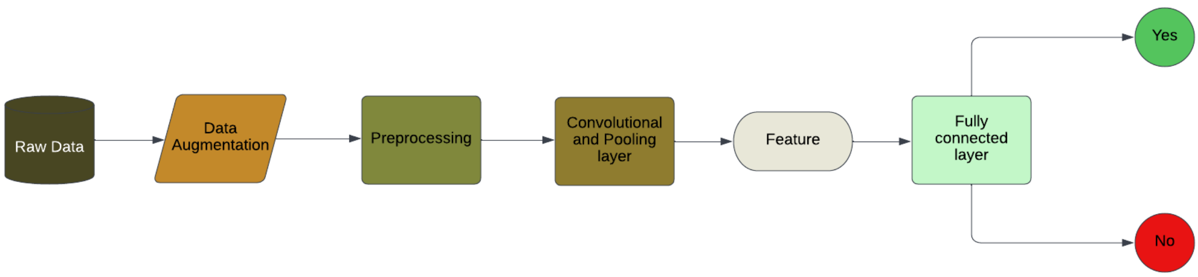
2.2 Proposed Methodology.

The use of convolutional neural networks (CNNs) for the automatic detection of brain tumors is a promising approach in the field of medical image analysis. CNNs are well-suited for this task because they are able to automatically learn spatial hierarchies of features from raw input images, allowing them to effectively distinguish between tissues that do not contain tumors and those that do.

In this study, input images were labeled with a binary (yes/no) classification, indicating whether they contained a tumor or not.

The CNN was then trained on these labeled images, using the patterns it learned to make predictions on new, unseen images. This approach has been shown to be effective in detecting brain tumors, and has the potential to improve the accuracy and efficiency of diagnosis in medical settings. The augmented dataset has 2318 images out of which 1240 are images having tumor in it and 1078 are images having no tumor.

Figure 2. Proposed methodology



2.3 Data Augmentation.

Augmentation is a common technique used in machine learning to improve the performance of a model by increasing the size and diversity of the training dataset. This is especially useful when the amount of available training data is limited, as is often the case with medical imaging data. By generating new data points through augmentation, a model can be trained on a larger and more diverse dataset, which can improve its performance on unseen data. In this paper, each image with a tumor is segmented into **8** images, and an image with no tumor is segmented into **11** images. After data augmentation, the dataset consists of **1240** samples containing tumors (53.49%) and **1078** samples not containing tumors (46.51%), bringing a total of **2318** images.

2.4 Image Pre-processing.

Image pre-processing is a crucial step in many image processing and computer vision tasks. It helps to improve the quality and consistency of the input images, making them more suitable for downstream analysis.

Pre-processing an image typically involves several steps, such as wrapping and cropping, resizing, and normalization. Wrapping and cropping is a process of identifying the main object in an image and adjusting the image so that the object is centered and fully visible. This is important because it ensures that the object of interest is not partially or fully outside of the image frame, which could lead to incorrect or incomplete analysis. After wrapping and cropping, the image is typically resized to a standard size, such as 240x240 pixels. This is important because it ensures that all images in the dataset have the same size, which is necessary for downstream analysis using machine learning algorithms.

Finally, the image is normalized, which involves scaling the pixel values to the range 0-1. This is important because it helps to improve the performance of machine learning algorithms by ensuring that the pixel values are in a consistent range.

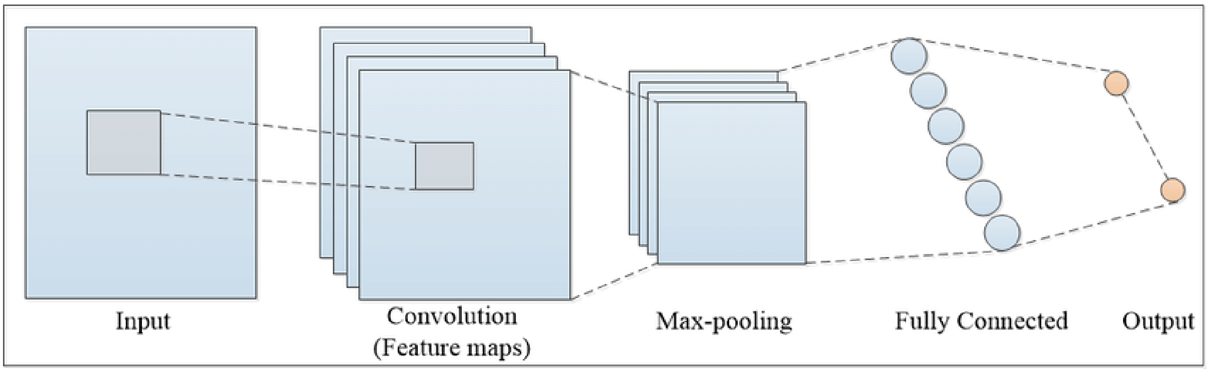
Overall, pre-processing is an important step in preparing images for downstream analysis, as it helps to improve the quality and consistency of the input data.

2.5 CNN Model.

CNN is a type of artificial neural network that is commonly used in image recognition and processing tasks. It is called a convolutional neural network because it uses a mathematical operation called convolution to filter the input data. In a convolutional layer, a filter or kernel is applied to the input data, which is typically an image, in order to detect certain features or patterns in the data. The convolution operation multiplies each element of the filter with the corresponding element of the input data and sums the results, producing a single output value for each position of the filter. This output is called a feature map, and it represents the detected features at each position in the input data.

The convolutional layer is followed by a pooling layer, which is used to reduce the dimensionality of the feature maps. Pooling can be performed in different ways, such as taking the maximum or average value of a group of pixels in the feature map. This step is important because it helps the network learn the most important features of the data and reduce the computational cost of the network.
After the pooling layer, the features are typically flattened into a one-dimensional vector and passed through a fully connected layer, where they are used to make a prediction or classification. This final layer uses the learned features to calculate the output probability for each possible class of the input data.

Figure 3. CNN Model



The flatten layer is used to flatten the output of the convolution and pooling layers into a one-dimensional vector, which can then be fed into a fully-connected dense layer for further processing. The dense layer performs a linear transformation on the input data, followed by an activation function that determines the output of the layer. In this case, the activation function used is the rule activation function.

The dropout layer is a regularization technique used to prevent overfitting in the model. It randomly sets a fraction of the input units to zero, effectively reducing the number of parameters in the model and forcing it to rely on a more distributed representation of the data. This helps to improve the generalization ability of the model and reduce overfitting.

In summary, the layers in the CNN model described in this research perform the following functions:

Convolution layer: This layer extract features from the input data
Pooling layer: reduce the dimensions of the data and make the model more robust to small changes
Flatten layer: flatten the output of the convolution and pooling layers into a one-dimensional vector
Dense layer: perform a linear transformation on the input data
Dropout layer: prevent overfitting in the model
Activation function: determine the output of the dense layer based on the rule activation function.

Figure 4. CNN Model Summary.

```
Model: "BrainDetectionModel"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_5 (InputLayer)        [(None, 240, 240, 3)]     0

 zero_padding2d_4 (ZeroPaddi  (None, 244, 244, 3)      0
 ng2D)

 conv0 (Conv2D)              (None, 238, 238, 32)      4736

 bn0 (BatchNormalization)    (None, 238, 238, 32)      128

 activation_4 (Activation)   (None, 238, 238, 32)      0

 max_pool0 (MaxPooling2D)    (None, 59, 59, 32)        0

 max_pool1 (MaxPooling2D)    (None, 14, 14, 32)        0

 flatten_4 (Flatten)         (None, 6272)              0

 fc (Dense)                  (None, 1)                 6273

=================================================================
Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64
_________________________________________________________________
```

3. Discussion

F1 score is a useful value to evaluate the performance of the system(model).

The F1-score combines the precision and recall of a classifier into a single metric by taking their harmonic mean.

F1 score and Accuracy are the statistical metrics used to find performance and efficiency of model.

The Actual dataset is consisting of 253 samples. But we have augmented the data into 2318 samples. Actual Positives (P), Actual Negatives (N), Predicted Positives (P') and Predicted Negatives (N') are few metrics involved in. True Positives (TP) are the positive samples which are correctly

labelled as positives. True Negatives (TN) are the negative samples which are correctly labelled as negatives. And FN, FP are the false negatives and false positives which are actually positives and negatives but are labelled as negatives and positives.

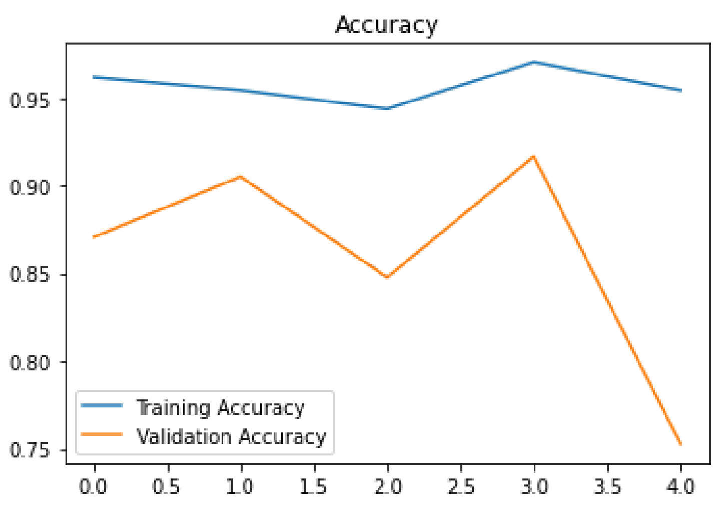
Accuracy is the efficiency of the model. It is the percentage of test set tuples those are correctly classified by the model.

$$P = TP + FN \quad \text{............(1)}$$

$$N = TN + FP \quad \text{............(2)}$$

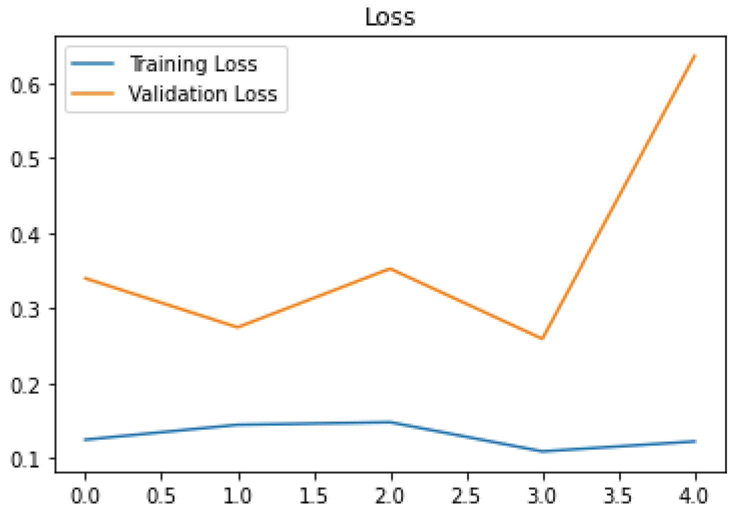
$$Accuracy = TP+TN/(P+N) \quad \text{............(3)}$$

Figure 5. Plot of Training Accuracy and Validation Accuracy



Loss is the value implies how poorly or well a model behaves after each iteration of optimization.

Figure 6. Plot of Training Loss and Validation Loss



Precision = TP/P′ ....(4)

P′ = TP + FP ....(5)

Recall = TP/P ....(6)

F1 – score = (2*precision*recall)/(precision + recall) ....(7)

F1 score that we achieved in the proposed model is **88.12%**.

Accuracy, Loss ratios of model in different epochs.

Table 1. Accuracy, loss for each epoch (set-1).

Epoch	Accuracy	Loss
Epoch – 1	0.6042	0.9271
Epoch – 2	0.7546	0.4983
Epoch – 3	0.7916	0.4610
Epoch – 4	0.8446	0.3734
Epoch – 5	0.8459	0.3498
Epoch – 6	0.8391	0.3693
Epoch – 7	0.8822	0.2842
Epoch – 8	0.8317	0.3613
Epoch – 9	0.9038	0.2587
Epoch – 10	0.9192	0.2225
Final	0.9192	0.2225

Table 2. Accuracy, loss for each epoch (set-2).

Epoch	Accuracy	Lose
Epoch – 1	0.9057	0.2442
Epoch – 2	0.9371	0.1887
Epoch – 3	0.9340	0.1826
Final	0.9340	0.1826

Table 3. Accuracy, loss for each epoch (set-3).

Epoch	Accuracy	Lose
Epoch – 1	0.9396	0.1656
Epoch – 2	0.9476	0.1548
Epoch – 3	0.9538	0.1471
Final	0.9538	0.1471

Table 4. Accuracy, loss for each epoch (set-4).

Epoch	Accuracy	Lose
Epoch – 1	0.9618	0.1243
Epoch – 2	0.9544	0.1442
Epoch – 3	0.9439	0.1476
Epoch – 4	0.9704	0.1086
Epoch – 5	0.9544	0.1220
Final	0.9544	0.1220

Table 5. Prediction Outcomes of Training, Validation, Testing.

	Yes	No	Total
Training Data	873	749	1622
Validation Data	186	162	348
Testing Data	181	167	348
Total	1240	1078	2318

4. Concluding Remarks

This model based on Convolutional Neural Networks (CNN) and the actual CNN are very useful tools for detecting and diagnosing brain tumors on MRI images. This study resulted in accuracy of 87% and a loss of 0.1220 from the total of 24 epochs and with batch size of 32. The number of convolution layers affects the quality of classification, but it is not the only factor that affects the quality of classification. Other factors, such as the number of filters in each convolution layer, the size of the filters, the stride, and the padding, can also affect the performance of a convolutional neural network (CNN). In general, increasing the number of convolution layers can improve the performance of a CNN, but there is a limit to the benefits of adding more layers. Beyond a certain point, adding more layers can actually decrease the performance of a CNN because of overfitting.

5. Future Work

Certainly, for future work more images can help improve classification results in many cases. In particular, using a larger and more diverse dataset can help a machine learning model generalize better and make more accurate predictions on new, unseen data. In addition to using more images, future studies could also incorporate other types of data, such as medical imaging data, patient records, and other relevant information.

As for classifying different types of tumors, this is an area that has received a lot of attention from researchers in the field of medical imaging and machine learning. By using advanced machine learning algorithms, it is possible to accurately identify and classify different types of tumors based on their appearance on medical images. This can be extremely valuable for diagnostic purposes, as it can help doctors make more informed decisions about how to treat their patients.

Overall, there are many exciting possibilities for using machine learning in the field of medical imaging, and I expect that we will see many more developments in this area in the coming years.

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