Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network

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***Abstract*— For successful treatment of the disease, accurate and early detection of brain tumours is essential. Early detection not only helps to come up with better medications, it can also save a life in due time. Neuro-oncologists are benefiting in many ways by the advent of Computer-Aided Diagnosis and biomedical informatics. Machine learning algorithms are recently have been put to use for processing medical imagery and information in contrast to manual diagnosis of a tumour, which is a tiresome task and involves human error. Computer-aided mechanisms are applied to obtain better results as compared with manual traditional diagnosis practices. This is generally done by extracting features through a convolutional neural network (CNN) and then classifying using a fully connected network. The proposed work involves the approach of deep neural network and incorporates a CNN based model to classify the MRI as "TUMOUR DETECTED" or "TUMOUR NOT DETECTED". The model captures a mean accuracy score of 96.08% with f-score of 97.3.**

Keywords*— *Machine Learning, Brain Tumour, Biomedical Informatics, CNN

I. INTRODUCTION

A brain tumour is a mass that develops inside the brain and is directly affected by the tissues underlying the brain or skull. The mass is broken down into two malignant and benign components. Such tumours grow irregularly in the brain and exert pressure. These triggers can cause many brain disorders. The number of people living in America with brain tumours is estimated at nearly 0.7 million in 2019. 0.86 Million such cases were diagnosed. 60,800 of these patients were listed as benign and 26,170 as malignant. The malignant patients ' survival rate in the US is 35% [14].

Accurate brain tumour MR images plays key role in clinical diagnosis and helps to take decisions for the patient treatment [2]. Manual brain tumour classification from MR images having similar structures or features is a complex and challenging task, depending on the radiologist's availability and experience to recognize and diagnose the brain tumour appropriately. Automated classification is a possible solution to address this problem by classifying brain tumour MR images with minimal human expertise interference in the related field.

Conventional classification methods in machine learning consist usually of confined steps including pre-processing, extraction of features, selection of features, reduction of dimensions and classification. The extraction of the feature usually comes with the level of expertise within the particular domain [4, 5]. Use of traditional methods of machine learning in this context is a challenging task for a non-expert. Deep learning algorithms and in particular CNN have shown remarkable success in bioinformatics, though relatively very fewer methods have been applied due numerous inherent challenges. CNN or ConvNet is a deep machine learning algorithm adopted to examine the images. We can identify, extract interesting and useful relationships and patterns from the data by using the data mining techniques. ML (machine learning) and data mining methods are being used successfully at an early stage for brain tumour identification and prevention. In our research, we deployed a CNN-based classifier, gathered from Kaggle that works on the classification principle of the given dataset. The model consists of three consecutive 2D convolution layers each having 2x2 kernels. A random division of database images into 70 percent and 30 percent was made, respectively, to shape the training set and validation set.

The remainder of the paper organisation is summarized as follows. Related work has been explained in section 2, section 3 has the suggested approach in machine learning, section 4 has the result and outcome and finally section 5 contains conclusion.

II. RELATED WORK

In 2019 for the classification problem via transfer learning, S. Deepak [1] proposed a pre-trained deep network framework, GoogLeNet, recording the mean accuracy of 98 percent. Transfer learning allows the use of a pre-trained CNN model, which was actually developed for another application. Transfer learning has proved its future in CAD of medical problems also.

Zhou et al. [2] used a pre-trained InceptionV3 model for identifying benign and malignant renal tumours on CT images.

G. Hemanth et al. [3] proposed a method which used a mean field term within the standard objective function of the CNN. The technique was developed and implemented by the use of the image processing method in MATLAB. UCI data sets are collected in contrast to various prevailing techniques, such as SVM (Support Vector Machine), CRF (Conditional Random Field and GA (Genetic Algorithm).

Unlike the current algorithms, the proposed CNN yields spontaneous performance.

Deep learning [4-8] shows impressive performance and generalizability through training on large amounts of data. This success is mainly due to rapid progress in computational power, especially through graphics processing units, which enabled the rapid development of complex deep learning algorithms. Several types of deep learning architectures were developed for various tasks including computer vision classification, speech recognition and object detection.

The proposed [9] classification of brain tumours was based on two-dimensional images, not 3-D volume, because in most clinical practices 2-D slices with a large slice gape are the acquired and available CEMRI images. To evaluate the performance it used five-fold cross-validation. The end result is the average accuracy of the five-fold test dataset in classification. The proposed block-wise fine-tuning transfer learning strategy suggests an alternative approach that is different from using pre-trained CNN as an off-the-shelf feature extractor (without training) that trains the separate classification method (such as SVM, k-NN, boosted trees, random forests and decision trees). It also demonstrates the ability of learning from natural images to medical brain MR images.

Sobhaninia et.al [11], proposed a novel method for CNN to automatically classify the most popular brain tumour forms, i.e., Pituitary, Glioma, Meningioma. They applied a linkNet network for tumour segmentation. 2100 images were used in network for training purpose. Twenty percent of them being validated and the remaining data are used for testing. Experimental network tests have shown that the 0.73 dice score for one network is met and 0.79 for multiple networks is achieved. In sagittal images, this comparatively high score was obtained by segmentation of tumours. Sagittal images contain no specifics of other organs and tumours are more noticeable than other pictures.

A new automatic segmentation based on the cascaded deep learning convolutional neural network has been developed by Cui et al. [12]. It contains intra tumour classification and tumour localization networks. The MRI tumour region is segregated via tumour localization and intra tumour classification network is able to mark the identified tumour area in several sub-regions. The research was conducted in the multimodal segmentation of brain tumours which included 220 cases of high grades glioma and 54 cases of low grade glioma. The assessment can be done by positive predictive value, sensitivity and dice coefficient.

Using SqueezeNet CNN architecture, fuzzy c-means method and extreme learning machine Fatih Özyurtbrain et al. [13] designed a system for classifying brain tumours. For detecting brain tumour, author proposed a model which is based on the Fuzzy C-means super-resolution (SR) and CNN algorithms with extreme machine learning algorithms. In the diagnosis of segmented brain tumours using FCM with SR, an accuracy rate of around 98.33 per cent was observed. The above detection rate is 10 per cent higher than the segmented brain tumour identification rate with non-SR FCM algorithms.

III. Proposed Work

Here, we proposed a model consisting of 3-layered CNN Architecture, which will later be connected to Fully Connected Neural Networks.

A. Convolutional Nueral Nets

CNNs are mostly used for deep neural networks. This consists of several nonlinear levels of operation, such as neural networks with many hidden layers. It can view images and frames from the film. CNNs learn the connections between pixels in the input image by extracting reflective attributes through pooling and convolution methods. The characteristics of each layer utilizing trained kernels differ in complexity, with simple elements like the edges extracted in the first layer and high level features extracted in the later layers. The pooling layer provides small shift invariance [10].

A computer treats an image as an array of pixels and relies on image resolution. Computer will see a height x width x dimension image. In CNN the image data depth is based on the number of image channels (3D and 2D for colour and grayscale images). For example, an image of a 6x6x3 RGB image matrix array and a 4x4x1 grey scale image matrix image array .Through CNN architecture [10], to predict performance, each input image is filtered by a series of layers such as convolution, pooling, and fully connected layers. It uses the function Softmax to classify objects with likely values between zero and one. The Fig. 1. shows the architecture of typical CNN.

B. Model Description

The model has been built on top of Keras, supported by Tensor flow at the backend, a simple python machine learning API. The model consists of 3 layers of CNN (2D convolution layer), each having 108, 64, 32perceptron. The shape of the input was defined as 366, 310, and 1 which corresponds to the image's width-height-grayscale nature. The kernel size has been deployed 3 X 3 and the Max_Pooling is used of 2 X 2 in the entire model.

Various Activation Functions have been used in the, they are:-

1) Rectified linear units (ReLU)

It is used in deep neural nets. Recently it has been shown to have six times improved convergence from the function of *Tanh*. Mathematically, Rectified liner units represented as:

$$R(x) = \max(0, x)$$
$$\text{If } x < 0,\ R(x) = 0 \text{ and } x >= 0,\ R(x) = x$$

2) Hyperbolic Tangent function- Tanh

Here, the output is zero based, since the range between -1 and 1. Optimization in this approach is easier therefore it is often favoured in practice over sigmoid function. Mathematically, Tanh represented as:

$$f(x) = \frac{1 - \exp(-2x)}{1 + \exp(-2x)}$$

3) Sigmoid Activation function

The range of sigmoid function is in between zero and 1. It is represented by S-shaped curve. Mathematically, it is represented as:

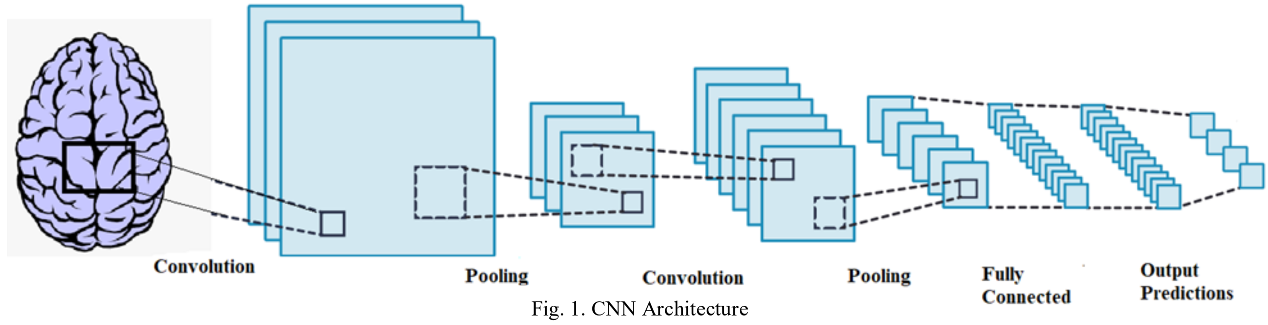

Fig. 1. CNN Architecture

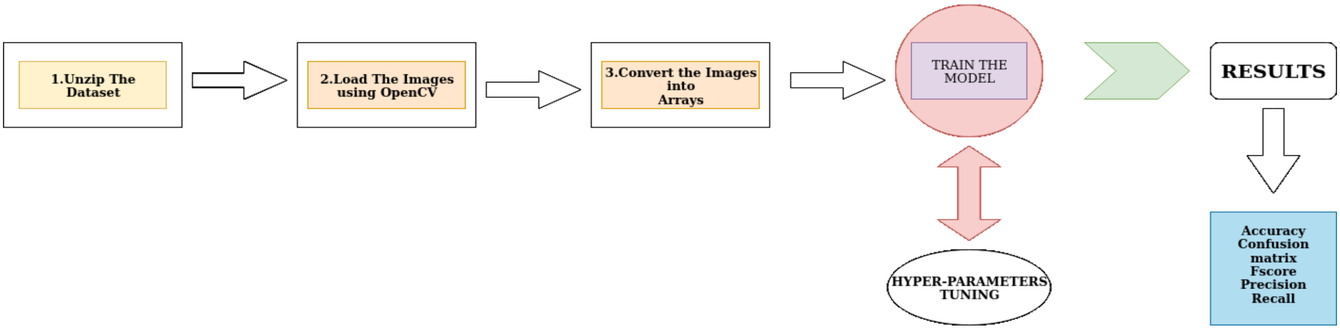

Fig. 2. The above picture presents at nutshell what the model is doing. Starting with the unzipping of the dataset, we first load the images using OpenCV library, a python library used to manipulate and work with image data. The images are converted into numpy arrays which are then feed to our CNN based model after proper pre-processing and train, test set splitting. Model tuning is performed. At the end metrics have been calculated and assessed.

$$f(x) = \frac{1}{1 + \exp(-x)}$$

The model has flattened layer, which is followed by densely connected neurons. Some of the perceptron has been dropped off in order to prevent overfitting. The loss function utilized the "binary_crossentropy" whereas the optimiser is ADAM.

The overall summary can be stated as:

TABLE I: SEQUENTIAL_9

Layer (type)	Output Shape	Params
conv2d_25 (Conv2D)	(None, 365, 309, 108)	540
activation_41 (Activation)	(None, 365, 309, 108)	0
max_pooling2d_25 (MaxPooling)	(None, 121, 103, 108)	0
conv2d_26 (Conv2D)	(None, 120, 102, 64)	27712
activation_42 (Activation)	(None, 120, 102, 64)	0
max_pooling2d_26 (MaxPooling)	(None, 40, 34, 64)	0
conv2d_27 (Conv2D)	(None, 39, 33, 32)	8224
activation_43 (Activation)	(None, 39, 33, 32)	0
max_pooling2d_27 (MaxPooling)	(None, 13, 11, 32)	0
flatten_9 (Flatten)	(None, 4576)	0
dense_17 (Dense)	(None, 200)	915400
activation_44 (Activation)	(None, 200)	0
dropout_9 (Dropout)	(None, 200)	0
dense_18 (Dense)	(None, 2)	402
activation_45 (Activation)	(None, 2)	0

Total params: 952,278
Trainable params: 952,278
Non-trainable params: 0

The overall Strategy can be understood by the Fig. 2.

IV. RESULTS AND OUTCOMES

Since this was a classification task of whether a brain tumour is malignant or not based on MRI images, we used some classical tools like accuracy, f-score, recall, accuracy, and confusion matrix to evaluate the model's performance. The model achieved a training accuracy of 97.47% in 35 epochs while the training loss was 0.402%.

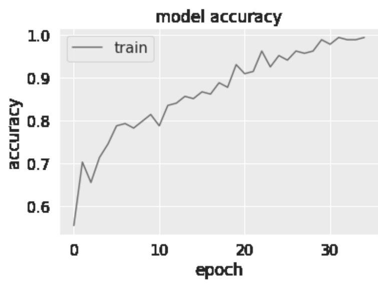

Fig. 3. Describes the training pattern of the model, which explains the accuracy of the model

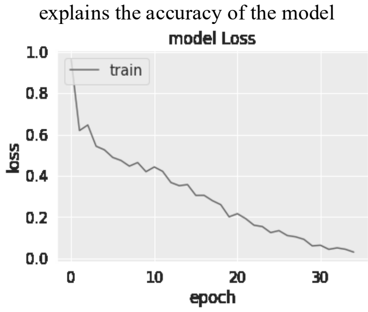

Fig. 4. Describes the model's training pattern, which explains the model's failure. It is clear that the loss was gradual and not too steep.

A. Confusion Matrix

It is quite evident from the confusion matrix that our model is, having 96.08 percent accuracy while error, can be given as 2.98 percent respectively.

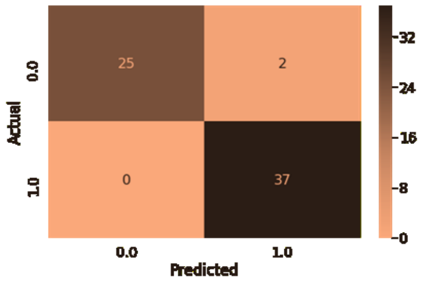

Fig. 5. Shows the confusion matrix of our model using seaborn.heatmap method

TABLE II: TESTING EVALUATIONS

Precision	0.9487179487179487
Recall	0.9863110487579402
F-score	0.9736842105263158
Error	0.0298388

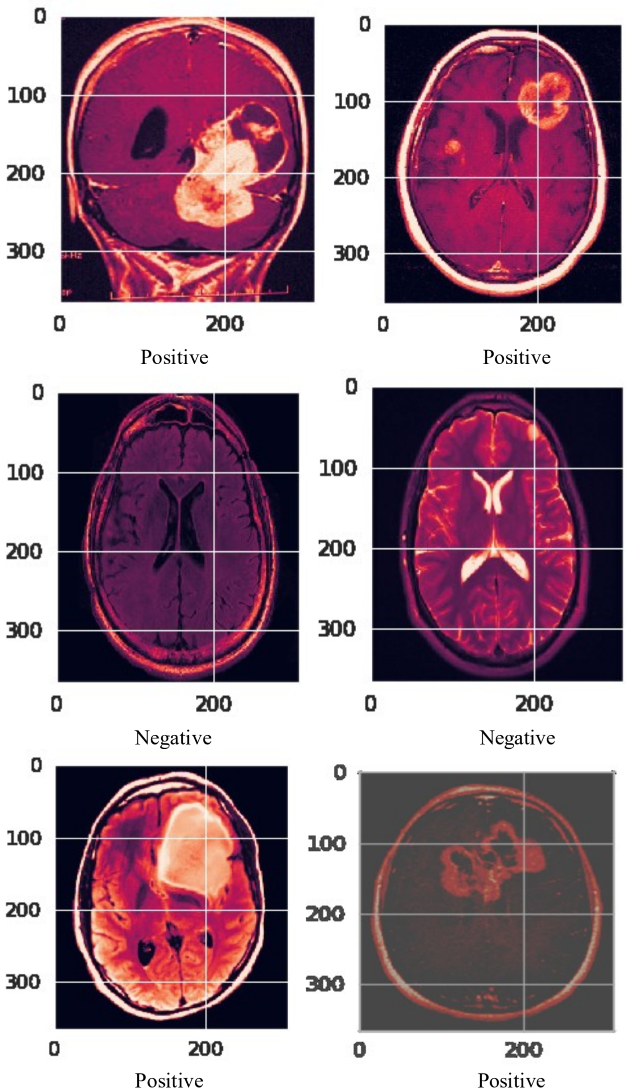

Fig. 6. Shows the test images from the dataset along with predicted label

V. Conclusion

In this research paper, we proposed a new system based on CNN, which discriminates between the Brain MRI images to mark them as tumorous or not. The model achieved the accuracy of 96.08%, with f-score of 97.3. The model is having CNN with 3 layers and requires very few steps of pre-processing to produce the results in 35 epochs. The purpose of the research is to highlight the importance of diagnostic machine learning applications and predictive treatment. We plan to detect brain tumour with neutrosophical principles in the future using the Convolutional Neural Network.

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