Brain Tumor Detector using Convolutional Neural Networks

Vishal Gupta, Amandeep

guptavishal2k@gmail.com, amandeep700933@gmail.com
Student, Btech CSE, LKCTC,Jalandhar, India

Abstract. This report presents and analyses the results of our brain tumour classification experiments. Resonance of magnetism. Imaging, or MRI for short, is a crucial medical imaging technology that provides finely detailed images of the internal organs of the human body using radio waves, a strong magnetic field, and a computer. This experiment uses a CNN (Convolutional Neural Network)-based deep learning model to categorise several kinds of brain tumours. An artificial neural network (ANN) that is frequently utilised for the analysis of photos and videos is called a CNN. It operates by using a technique known as convolution to take an input image and divide it into smaller components.
At 97.142%, the proposed idea achieves a noteworthy accuracy. The confusion matrix is used to gauge accuracy. Any machine learning model's performance can be examined using this table. This compares a dataset's actual values with the model's projected values and presents the findings in an understandable and structured manner.

Keywords: MRI, Convolutional Neural Network (CNN), Brain Tumor Detection, Deep Learning.

INTRODUCTION

The process of locating and classifying tumours that start in the brain or other central nervous system regions is known as brain tumour detection. Brain tumours come in a variety of forms, and they are divided into groups according to many traits like behaviour, cell type, and where in the brain they are located.

Brain tumours can be classified according to their molecular or genetic features, location, type of cell, behaviour, and mutations. This classification aids medical professionals in creating individualised treatment regimens for each patient. Through machine learning, computers can be specifically trained to learn from data and make predictions or choices. In domains such as healthcare, deep learning algorithms have the capacity to handle and evaluate enormous volumes of data and generate insightful conclusions or forecasts. Although several designs and algorithms have been used in the past to create the brain tumour classification system, more recent efforts have increased accuracy[1].

By correctly classifying brain tumours, medical professionals can create individualised treatment regimens that are suited to the requirements of each patient. Healthcare, banking, and self-driving car technologies are just a few of the industries that machine learning and deep learning algorithms have the potential to completely transform.

METHODOLOGIES

Figure 2.1 illustrates the recommended procedure, which begins with loading and extracting the dataset's raw files' photos and annotations. This dataset is then split into subsets for training, testing, and validation before preprocessing and augmentation techniques are applied. After that, the structure of the suggested method is presented, and optimisation methods, regularisation strategies, and hyper-parameters are adjusted[4]. The findings of network training and performance calculations are presented in the paper's conclusion.

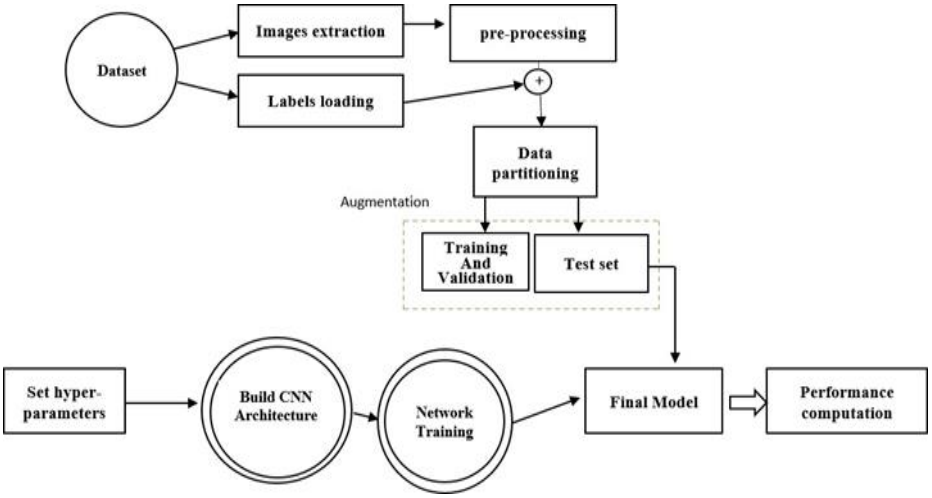

Figure 2.1. Block Diagram of the System

DATASET

In order to build the CNN, we used data from Kaggle, which included about 3300 brain MRI pictures classified as pituitary tumours, glioma tumours, meningioma tumours, and no tumours at all. We then used Keras, an easy-to-use Python neural network (NN) library, to create 2880 training and 384 testing models[19]. Two convolution layers make up the model architecture, and the softmax layer provides the likelihood that an MRI falls into one of the four categories. With only ninety-nine epochs, our simple model managed to reach an accuracy of about 97.143.

METHODS

Convolutional Neural Network

The architecture of ConvNets was inspired by the structure of the visual cortex, which is modelled after the neuronal connectivity found in the human brain. the duration of a single neuron's response to an input. The entire viewing region is covered by overlapping receptive fields. In comparison to other activation functions, each function is a non-saturated function that significantly accelerates training.

Soft-Max Layers

In neural networks, the softmax layer is a mathematical function that is frequently used for multi-class classification tasks like classifying brain tumours. The output of the preceding layer, which is usually a set of numerical scores or logits, is transformed into a set of probabilities that add up to one by the softmax layer[6]. The softmax layer applies the softmax function to the neural network's final output, a vector of numerical scores that represent various tumour kinds, in the context of classifying brain tumours. As a result, a vector of probabilities representing the chance of each type of tumour existing in the input image is produced.

Recurrent Neural Network

Recurrent neural networks (RNNs) are a type of neural network that can analyse sequential data, which is useful in medical imaging applications where the input data is often a sequence of images. RNNs can be used to classify brain tumours by analysing the temporal sequence of MRI scan pictures to determine the kind and presence of the tumour. Numerous research works have investigated the application of RNNs in the categorization of brain tumours. The LSTM-based approach outperformed other machine learning models and attained excellent accuracy in tumour categorization. RNN-based models have demonstrated potential in the categorization of brain tumours and may prove to be a helpful diagnostic and therapeutic tool for brain tumours[21].

One Hot Encoding

Label encoding gives each category in a column a numerical value; nevertheless, this can lead to issues if algorithms perceive the values as belonging to a hierarchy or order. One-Hot Encoding is a popular alternate technique that addresses this problem by giving each category a new column and a binary value of either 1 or 0[9]. However, if a column contains a large number of unique values, this strategy may result in a huge increase in the number of columns in the data set. Since the SciKit library's OneHotEncoder can only handle numerical categorical values, string values must first be label encoded before they can be one-hot encoded.

64 Base Decoder

One technique for converting binary or text data into ASCII characters is base64 encoding. The accuracy with which the data is processed by various systems is improved by this conversion. However, the method of decoding a Base64 string is the opposite of encoding it. The Base64 strings are transformed into an object that resembles a string after first becoming unencoded data bytes. The Base64 string can be decoded using the procedures stated below: First, the decimal values of the characters in the string are computed[18]. The decimal values that were received are then converted to their binary equivalents. The first two bits of each binary number are truncated, and the remaining sets of 6 bits are merged to make a long string of binary numbers. Finally, the long binary string is split up into groups of eight bits.

EXPERIMENTAL RESULTS

Accuracy and Loss

The accuracy development and loss for our proposed network during the validation phase are shown in the image below. The first figure 5(a) shows that the curve initially starts at zero but gradually increases with time, with a phase-average accuracy of 97.143%.

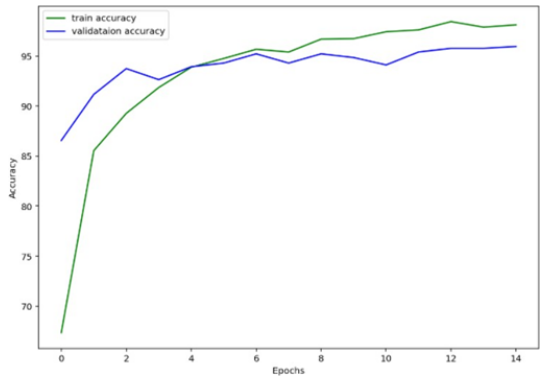

Figure 5(a) Train and variation accuracy

And in the figure 5(b) we can see the total loss we have gained during the final stage of the project. The loss we have achieved is around 0.142% which is better than the previously built projects. Overall, the accuracy we received is more than other projects proposed in past. The loss we received is also less than compared to other publishers[5].

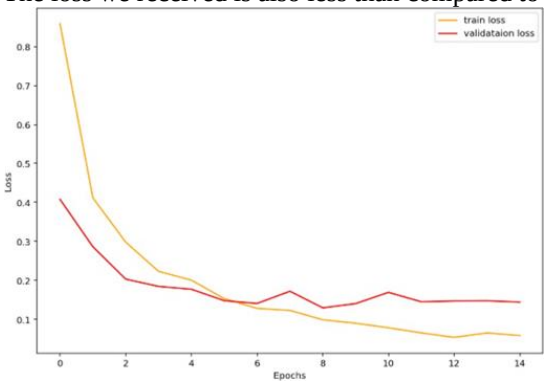

Figure 5(b) Train and Variation loss

Confusion Matrix

The Confusion matrix, which displays the effectiveness of our suggested project, is shown in figure 5(c). In equation 5, the genuine labels, or ground truth, are displayed on the y-axis, while the anticipated readings, or system output, are represented on the x-axis. Sensitivity, specificity, accuracy, and precision calculations have been performed using this form.

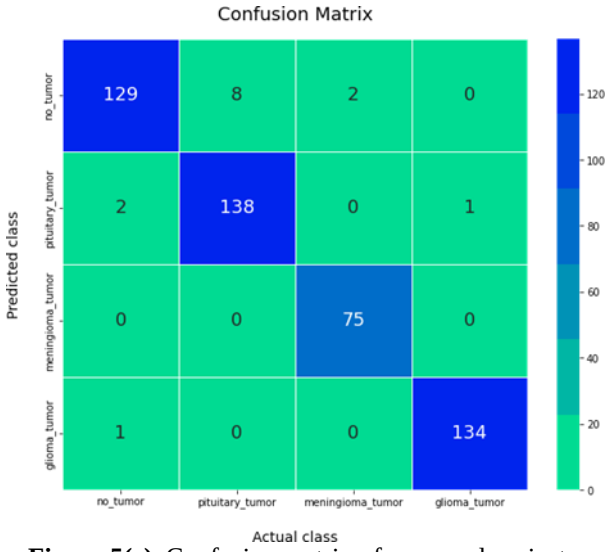

Figure 5(c). Confusion matrix of proposed project

Table 1. Accuracy Matrix

	Precision	Recall	F1-Score	Support
No_tumor	0.98	0.93	0.95	139
Pituitary_tumor	0.95	0.98	0.96	141
Meningioma_tumor	0.97	1.00	0.99	75
Glioma_tumor	0.99	0.99	0.99	135
Accuracy			0.97	490
Macro avg.	0.97	0.97	0.97	490
Weighted avg.	0.97	0.97	0.97	490

Tools and Time Consumed

The proposed system is trained on Intel i7(2.8 GHz), 4GB GPU and 8GB RAM. Python and VS Code. The training time was approx. 166 minutes for the whole dataset and average test execution time was 1s 54ms per image.

CONCLUSION

By allowing people to contribute brain MRI pictures, this study provides a system for identifying brain tumours that can identify whether a person has gliomas, meningiomas, pituitary tumours, or no tumour at all. The expected results as well as interesting information regarding the type of tumour (if any) are presented on the web application. The website comprises a header, two instruction steps, an upload button where users can upload MRI images[12], and four display areas where the user can view the uploaded MRI image, the predicted result, the second predicted result, and interesting details about the tumour type (if any). The MRI picture that was uploaded is transformed into an array, reshaped to the model's needed input shape, and afterwards applied to forecast. Next, the online application displays the forecast result. If a glioma, meningioma, or pituitary tumour is the anticipated tumour type, some fascinating details regarding the tumour kind are also shown. Due to the many imaging views, the dataset is not very large; however, the application of data augmentation substantially improved the results and assisted in resolving this issue. We have used the dataset from this study to attain an accuracy of 97.143% for our suggested project.

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