Multi-Class Classification of Brain Tumour

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Abstract

With the ever-increasing population all over the world there is enormous research going on in the field of medical sciences. There are large number of outbreaks in different parts of the sphere in terms of pandemics and epidemics. There is innovative probing being done in order to tackle the problem. Out of the lot, most of the ailments are obstructive and might affect at the cost of lives. In this category of obstructive diseases, heart disorders, lung disorders and brain disorders count in majorly. Worldwide, an estimate 251,329 people died from primary cancerous brain and CNS tumours in 2020. In order to tackle this problem, there are various methods proposed both with respect to medical field as well as technological field. This paper proposes a solution to categorize brain tumours and efficiently detect them as early as possible.

Index Terms

Brain tumours, MRI Scans, Deep Learning, CNN

I. Introduction

With the incredibly growing number of diseases worldwide, the field of health-care has been progressively growing in the way we look at diseases and their detection. The area of medicinal sciences deals with the detection, diagnosis and treatment of diseases, disorders, and ailments. It studies the molecular breakdown structure of any disease and works towards the development of drugs and pharmaceuticals. There are different branches contributing to this main field like curative healthcare and preventive healthcare. Due to boundless outbreaks of varieties of diseases, there are infinitely emerging symptoms which are difficult to keep track of. This also leads to the tough task of conducting tests and detecting the existence of a disorder.

Among all classes of maladies, the one which is considered as an important category is diseases related to Brain Tumours. There are different variations in this class of tumours namely, Glioma tumour, Meningioma tumour and Pituitary tumour.

Considering the intrusive effects of the disease, there always exists a need of call to proper detection, diagnosis and curing of any disease. As known, doctors' expertise this field and can help. When a patient after noticing symptoms or changes approaches a medical practitioner, he would be counselled asking for signs he is experiencing followed by a number of questions which would help a doctor to understand a victim's condition better and treat him upon that. After this several tests are to be conducted based on physician's prescription to conclude the result on existence of a disease and the intensity of the same.

The primary step of interest is the detection of disease. Any obstructive disease can't be identified by just knowing the symptoms; therefore, tests are necessary. There are two levels of tests generally performed. The first is preliminary screening test, wherein the presence of a disease can be identified by at most one test. This would not lead to confirmation of a disorder but would act as a path for further confirmatory tests to be performed.

Screening or confirmatory tests would require some input to carry out the procedure. In majority of the cases the data is in the form of images i.e., Chest X-Ray, Computed Tomography (CT) scan or a Magnetic Resonance Images (MRI). With regards to the brain tumour detection MRI scans are used.

Due to the ever-increasing population and constraints on time and cost, even though there are a number of radiologists and doctors who could read a scanned image and tell the results to the patient, there are deaths which are caused due to the severity of a patient or his hindrance in going to a physician. The doctor to patient ratio in India is 1:1456 roughly as per WHO, to increase the efficiency and save time

automation is necessary. Technically identifying a disease atleast to suffice as a screening test is required to save time and effort of a doctor. Doctors are looking for some technology which could automate the process to save time and intensive research is going on regarding the same.

Though there are many innovations done technically they were able to binary classify an MRI image as affected or not [1], but there is also a need to classify the type of brain tumour as treatments would vary from one class to another.

The design goal of this research is not only to identify the tumour but also to classify the kind of brain tumour through MRI scan. This project makes use of CNNs, Transfer Learning and libraries like TensorFlow Keras.

Rest of this paper is organized as follows: Section II deals with related work. The design of the project is presented in Section III. Section IV deals with the implementation. Experimental results are presented in section V. Overall summarization of the paper and future directions are presented in section VI. References are mentioned in section VII.

II. RELATED WORK

Brain tumour detection and categorization is one of the important areas to research and work in the field of technology and medical sciences. In order to detect it from the technical aspects Image Processing and CNNs can be used. Coming to the multi-class classification wherein a particular input image may belong to exactly one class of the many classes, classification supervised algorithms like SVM could be used. The results would not be always accurate, this would be due to low radiation, high contrast and spatial resolution of the MR images [2].

With a human naked eye, it is not possible to diagnose a tumour in all slices. Hence, an expert radiologist is required for accurate identification of a brain tumour. Therefore, the automated systems are always required to diagnose a tumour in the MR images without human intervention.

The detection of the variation of tumour can be also done using a pre-trained deep learning model, Besides, the classification accuracy of tumour type classification is increased when a pretrained model is trained by extracted tumour images but on the other hand, the classification time is increased as compared to trained pretrained model by original MRI scans [3]. Cost and time act as critical constraints to the problem and are to be handled properly. Some of the pre-trained convolution neural networks like AlexNet, GoogleNet and VGG19 could be used for Brain Tumour classification. One neural network named BrainMRNet which used attention modules, residual blocks and hyper-column technique achieved greater accuracy in classification compared to other pre-trained models [4]. Using the hyper-column technique, feature maps extracted at each stage in the model were transferred to the sequence structure in the last layer. By using residual blocks, the steps that negatively affect performance in the depth of the model were minimized. Transfer learning method was used in this architecture. With the proposed model it was not possible to use it on different medical images and in different fields.

A novel approach proposed based on long short-term memory (LSTM) model can be used for classifying magnetic resonance images (MRI). MR images are captured in a sequence, and LSTM is more helpful to learn the sequences of this type of data. This model consisted of input layer, four LSTM layers, a fully connected, a SoftMax and a classification layer [5]. Each layer contains s LSTM blocks. Each block contains four gates including an input (I), a forget (F), a cell candidate (g) and an output (O) gate as shown in Fig. 1 below.

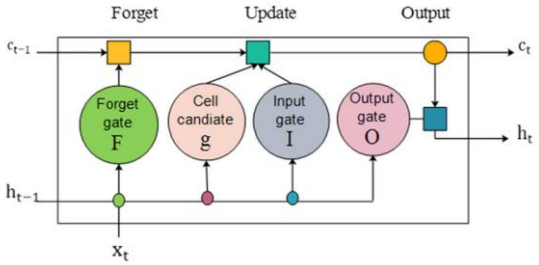


Fig. 1: Overview of the LSTM block

This work does not classify tumours in sub-tumoral region and it does not account the severity level of the tumour region.

Pros and cons of various methods provokes usage of Hybrid approaches. In this approach more than one CNN model or an architecture is

combined to obtain the required results. Resnet50 architecture, one of the CNN models, is used as the base. With this model, 97.2% accuracy value is obtained [6]. Using this approach Mistakes that may arise in traditional methods are prevented. The data set is classified primarily with the CNN models, Alex net, Resnet50, Densenet201, Google net and InceptionV3 models. This paper doesn't include multiclass classification as well as grade levels of tumour classification hasn't been considered.

III. DESIGN

This section describes various design principles used in the development of Brain Tumour MRI Multi-Class Classification.

The research design refers to the overall strategy that the project has chosen to integrate the different components of the study in a coherent and logical way, thereby, ensuring effectively addressing of the research problem.

The overall architectural diagram is shown in the below Fig 2.

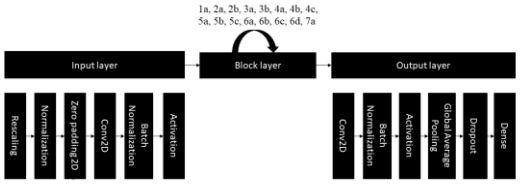


Fig 2. Architectural Design

IV. PROPOSED METHODOLOGY

This section describes the implementation details of this project. It deals with the methodology applied.

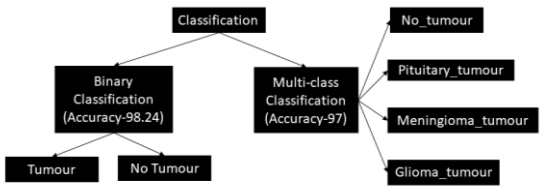


Fig. 3: Overview of classification

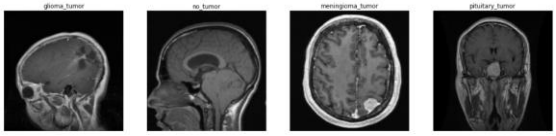
Fig 3 above shows the general flow of the classification.

Data Exploration

Professional MRI scans:

- Taken in different angles
- 2D images in greyscale
- 3275 MRI brain scan images
- Split 80-20 for training and validation.

Sample images of each class



Steps involved in building the project:

1. Initial exploration of the problem and the data set.
2. Data préparation by resizing and shuffling.
3. Start building a CNN model manually via transfer learning.
4. Compilation of the model using optimizers and callbacks.
5. Prediction and evaluation of the trained model.

The entire project is carried out in two steps, viz.

- Feature Extraction
- Classification

The exact proposed methodology is shown in Fig 4 below.

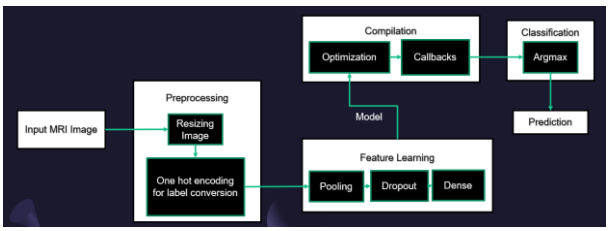


Fig. 4: Proposed methodology

Firstly, an MRI scan is taken as input, then pre-processing steps are applied. First the image is resized using an OpenCV object and one hot encoding technique is applied for the numerical conversion of the labels.

For the purpose of classification, under transfer learning approach an EfficientNetB0 model is being used in this project. This is made up of 3 important layers. The model is built using

layers like GlobalAveragePooling2D, dropout and Dense. GlobalAveragePooling2D layer acts like the Max Pooling layer in CNNs, the only difference being is that it uses the Average values instead of the Max value while pooling. This really helps in decreasing the computational load on the machine while training. Dropout layer omits some of the neurons at each step from the layer making the neurons more independent from the neighbouring neurons. It helps in avoiding overfitting. Neurons to be omitted are selected at random. The **rate** parameter is the likelihood of a neuron activation being set to 0, thus dropping out the neuron. Dense layer is the output layer which classifies the image into 1 of the 4 possible classes. It uses the SoftMax function which is a generalization of the sigmoid function.

The summary of the final model built is given in Fig 5. There are some rescaling and normalization layers at the beginning, followed by the same layers with same parameter values are used for blocks 1a, 2a, 2b, 3a, 3b, 4a, 4b, 4c, 5a, 5b, 5c, 6a, 6b, 6c, 6d, 7a and finally have global average pooling, dropout and dense layer at the end.

Layer (type)	Output Shape	Param #	Connected to
input_3 (InputLayer)	[(None, 150, 150, 3)]	0	[]
rescaling_2 (Rescaling)	(None, 150, 150, 3)	0	['input_3[0][0]']
normalization_2 (Normalization)	(None, 150, 150, 3)	7	['rescaling_2[0][0]']
stem_conv_pad (ZeroPadding2D)	(None, 151, 151, 3)	0	['normalization_2[0][0]'
stem_conv (Conv2D)	(None, 75, 75, 32)	864	['stem_conv_pad[0][0]']
stem_bn (BatchNormalization)	(None, 75, 75, 32)	128	['stem_conv[0][0]']
stem_activation (Activation)	(None, 75, 75, 32)	0	['stem_bn[0][0]']
block1a_dwconv (DepthwiseConv2D)	(None, 75, 75, 32)	288	['stem_activation[0][0]'
block1a_bn (BatchNormalization)	(None, 75, 75, 32)	128	['block1a_dwconv[0][0]']
block1a_activation (Activation)	(None, 75, 75, 32)	0	['block1a_bn[0][0]']
block1a_se_squeeze (GlobalAveragePooling2D)	(None, 32)	0	['block1a_activation[0][0]']
block1a_se_reshape (Reshape)	(None, 1, 1, 32)	0	['block1a_se_squeeze[0][0]']
block1a_se_reduce (Conv2D)	(None, 1, 1, 8)	264	['block1a_se_reshape[0][0]']
block1a_se_expand (Conv2D)	(None, 1, 1, 32)	288	['block1a_se_reduce[0][0]']
block1a_se_excite (Multiply)	(None, 75, 75, 32)	0	['block1a_activation[0][0]', 'block1a_se_expand[0][0]']
block1a_project_conv (Conv2D)	(None, 75, 75, 16)	512	['block1a_se_excite[0][0]']
block1a_project_bn (BatchNormalization)	(None, 75, 75, 16)	64	['block1a_project_conv[0][0]']
block2a_expand_conv (Conv2D)	(None, 75, 75, 96)	1536	['block1a_project_bn[0][0]']
block2a_expand_bn (BatchNormalization)	(None, 75, 75, 96)	384	['block2a_expand_conv[0][0]']
block2a_expand_activation (Activation)	(None, 75, 75, 96)	0	['block2a_expand_bn[0][0]']
block2a_dwconv_pad (ZeroPadding2D)	(None, 77, 77, 96)	0	['block2a_expand_activation[0][0]']
top_conv (Conv2D)	(None, 5, 5, 1280)	409600	['block7a_project_bn[0][0]']
top_bn (BatchNormalization)	(None, 5, 5, 1280)	5120	['top_conv[0][0]']
top_activation (Activation)	(None, 5, 5, 1280)	0	['top_bn[0][0]']
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 1280)	0	['top_activation[0][0]']
dropout_2 (Dropout)	(None, 1280)	0	['global_average_pooling2d_2[0][0]']
dense_2 (Dense)	(None, 4)	5124	['dropout_2[0][0]']

Total params: 4,054,695
Trainable params: 4,012,672
Non-trainable params: 42,023

Fig. 5: Model summary

This created model is compiled in order to improve its performance and accuracy. To achieve this certain compilation steps like optimization and call-back mechanisms are applied. Optimization is done using an Adam optimizer. A call-back is a set of functions to be applied at given stages of the training procedure. Call-backs could be used to get a view on internal states and statistics of the model during training. Tensor Board, Model Checkpoint and ReduceLROnPlateau call-back functions are used here. Finally, the model is trained with 12 epochs under a batch-size of 32 with the mentioned call-backs as the parameters. For the purpose of prediction, argmax function is used as each row from the prediction array contains four values for the respective labels. The maximum value which is in each row depicts the predicted output out of the 4 possible outcomes.

V. Results

This section presents the experimental results of the implemented solution.

There are different metrics used for the evaluation of the model at each stage of tuning.

Metrics like Confusion Matrix, Accuracy, and Classification Report are used.

Solution summary of the model:

A Convolutional Neural Networks using transfer learning for multi-classes classification used in this project is a deep learning technique with high potentials to be tuned for increased accuracy.

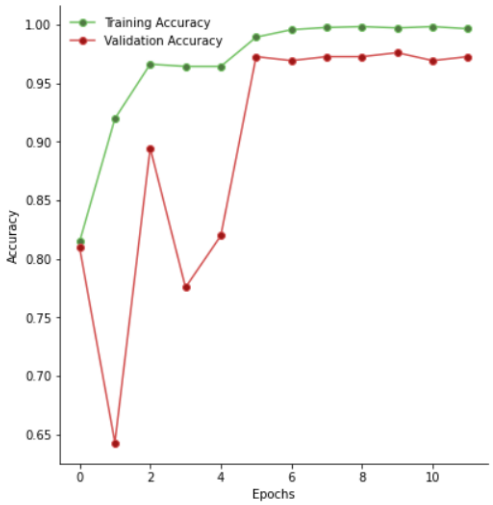


Fig. 6: Accuracy plot

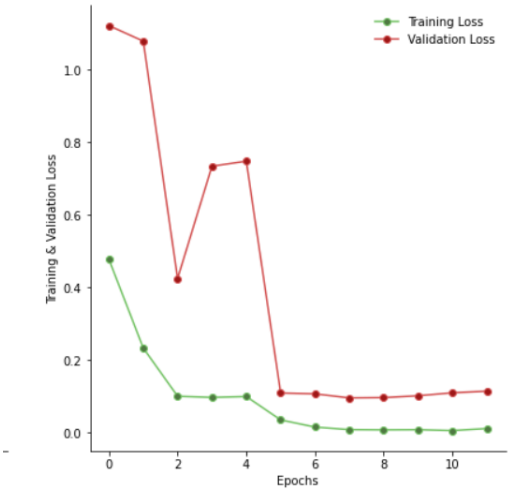


Fig. 7: Plot for loss

The plot in Fig 6 above shows accuracy plots of training and testing data similarly plot in Fig 7 shows plots related to losses of testing and training data.

Image in Fig 8 depicts confusion matrix as a Heat map of the same model.

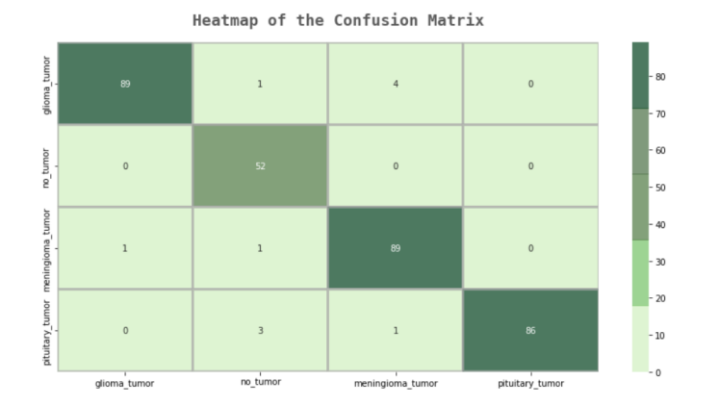


Fig. 8: Confusion matrix of model

Classification report of the model is as follows in Fig 9,

	precision	recall	f1-score	support
0	0.99	0.95	0.97	94
1	0.91	1.00	0.95	52
2	0.95	0.98	0.96	91
3	1.00	0.96	0.98	90
accuracy			0.97	327
macro avg	0.96	0.97	0.97	327
weighted avg	0.97	0.97	0.97	327

Fig. 9: Classification report of model

As seen the model gave an accuracy around 0.97.

VI. Conclusion and Future Scope

This project developed a solution for multi-class classification of brain MRI scans into 4 kinds of tumours including normal ones. Automated classification ML/Deep learning models such as, Convolutional Neural Network (CNNs)works well in image classifications and object detections. Libraries like TensorFlow Keras and compilation techniques, embrace the possibility of quick optimization of the classifier with millions of combinations in hyperparameters.

Future scope would require focusing on implementing the same method to multiple diseases. Also, rather than classifying only the kind of tumor the grade or level of that tumor can also be predicted.

VII. References

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