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Brain tumour Detection Using Deep Models

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ABSTRACT

Brain tumour is a kind of tumour which affects the brain tissue and spreads along time varying regenerative disease. If not detected in particular time limit it will be out of control and results in further death. So, instead of neglecting this disease we can detect this disease using our method computer aided diagnosis where doctor / radiologist is absent. If this brain tumour is detected in early stage is sometimes be cured.
In this project we introduced two deep learning models. primary model is for converting small unbalanced dataset to large balanced dataset of MRI images i.e.., using Modified Convolutional Variational Auto Encoder(CVAE). The second Model is used for detection and classification. The first model is generative model and another model is used for Training and classification using the classifier of Residual Network Model (RESNET). By using these two deep models higher Performance of model is achieved. The proposed framework has an accuracy of 99%.

Keywords : Brain Tumour, Convolutional Variational Auto Encoder, latent space, Synthetic- images, Generator model, Classifier Model.

I. INTRODUCTION

Recently the brain tumour cases were rapidly increasing in our present era. The brain tumour is classified into There were various causes for brain tumour among them some were due to the change in gene. According to the classification standards from WHO brain tumours are classified into 4 grades from benign1 to malignant 4 grades. With deep neural networks, high level features extracted from the MRI images are utilized to categorise the different grades that may help radiologists in making decisions about early diagonosis and future treatment.

Magnetic Resonance Imaging (MRI) has got a much importance in our present modern era when compared to the X-Ray, CT-Images, etc..., based on the intensity of the rays, and their side effects over human bodies. Apart from this MRI images also provide high contrast to soft tissues in brain. MRI images has various gray levels in it which defines the depth of the tissues and diseases in body, which is one of the Computer Aided Diagonosis(CAD). In CAD

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systems Machine Learning algorithms were generally prefered to detect & classify brain tumours.

The basic step for these systems are extracting the features from the input MRI images. Then these extracted features are then fed into structured model to detect and classify brain tumours.

II. RELATED WORK

Deep learning methods can helps to solve many problems based on Computer Aided Diagnosis (CAD) by extracting the features from the Raw MRI images directly. Convolutional Neural Network (CNN) is generally used deep model in these systems [12]. CNN can automatically learn the complex features from image itself. CNN based tumour detection includes two phases. First is training of those images. Second is classification in which the images has tumour or not. In [5] authors used two different models for developing accurate brain tumour detection with classification. But in these models they used one model for extracting features in images and reconstructing them, the other model is training the model using the reconstructed images. The CNN and its variants were incapable of improving the performance of the outputs. This is because of the CNN and deep models were data hungry they need more number of samples for good performance.

III. PROPOSED WORK

The proposed framework takes brain MRI images dataset collected by traditional MRI-based systems as input, typically class unbalanced and small in size. These input images were passed through the pre-processing block. The framework contains two Deep Models, namely., The Generator model and Classifier model. The generator learns the distribution of the important features in the pre-processed images. Then given the distribution of important features, the generator can convert the small unbalanced dataset to large balanced dataset. This large balanced dataset is used to train the second deep model classifier which is used for detection and /or classification.

3.1. INPUT DATA :-

The input to this system is a set of brain MRI images. This set is small and imbalanced w.r.t. number of training images in class. The MRI images are stored as two –dimensional (2D) gray-scale images .These grayscale images stores values of 0-255 Almost all MRI scanner outputs were of standard medical format.

3.2. PREPROCESSOR MODULE:-

This module is used to resize and normalise input MRI images. The grayscale input images were resized to size of 256x256 pixels. These images are fed to deep model with fixed input size. Then normalising the input data speeds up learning and faster convergence. The grayscale input images were normalised to be in the range [0,1]. The normalisation is defined in intensity values. A minimum-maximum normalisation technique is used to scale the intensity values of 0 and 1. Then these images were passed through the generator network.

3.3. GENERATOR MODEL :-

The aim of generator model is to synthesize new brain MRI images for each class. The generator model is trained using preprocessed images and generates a new MRI images which resemble to typical patterns of images from preprocessed layer. The auto encoders are a specific type of feed-forward neural networks where the input is similar to the output. There are used to learn the features from the dataset images with a low-dimensional latent space in an unsupervised manner. Here they compress the input image into low dimensional embeddings(Latent space representation) and reconstruct the output image from this embeddings. This latent space learns to capture the most important information for image reconstruction. These embeddings will be rarely distributed that makes key information to spread across various clusters in this embeddings. In mean time this empty space between the clusters doesnot have any information which makes sampling from it results in meaningless results.

To overcome this problem faced from the auto encoders we use the Variational Auto Encoder(VAE) [17]. In Variational auto encoder a new parameter is added that the latent space embedding to follow certain predefined distribution usually normal distribution [17]. Now these embeddings follow the normal distribution the network is now forced to utilise this space so, that the information is distributed. That allows us to sample from any point in this space to generate new images which reflects the images pattern from the original small brain MRI images dataset. Hence we use this VAE model to generate new MRI images.The convolutional and de-convolutional layers are applied in implementation of encoder and decoder instead of our regular feed forward layers. Because, as the brain tumours will not be of same size, shape, same number, same place. These above layers uses sliding filter maps that recognise the tumour local patterns independently of their number, shape and position in the brain MRI images. The below figure 1 shows the architecture of the Generator network model of Convolutional Variational Auto Encoder (CVAE). This CVAE network has two components. The first is encoder and second is decoder. The encoder network contains many convolutional layers followed by the fully connected layer. While decoder consists of fully connected layer followed by deconvolutional layers. The encoder compresses the input brain MRI images to hidden representation(latent) and network parameters as output. This latent space is refer to as bottleneck as the encoder must learn the efficient compression of the input images into the lower dimensional space. We can refer encoder As the ratio of latent space to the input image Qφ(z|x). We can sample the distribution of noisy values to get values of representation z. Next the decoder takes this latent space representation as input and produce the parameters to the probability distribution function of images and have weights and biases θ. The decoder is denoted as Pθ (x|z). The loss consists of two terms .The first loss is forcing the encoder to learn to produce new images instead of meaningless images from space embeddings.The second loss term is a regularizer which is the divergence between the encoder distribution and predefined distribution. Here =N(0,1) the regularizer forces the embeddings to follow the standard normal distribution

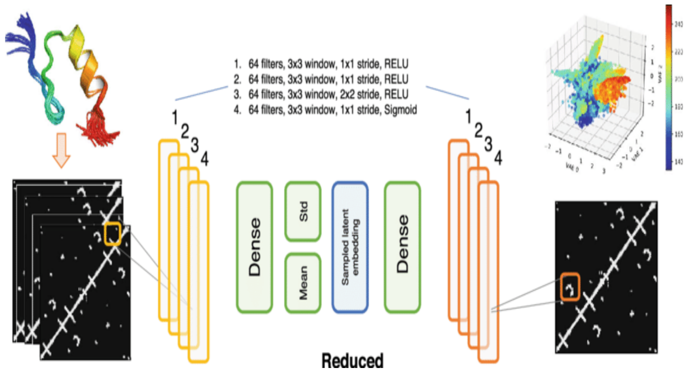


Fig.1. Generator Model- Modified Convolutional variational auto encoder

A Convolutional Variational Auto Encoder model is employed for each class in dataset to learn this joint distribution of input features from the small input imbalanced dataset of MRI brain images. After finishing the training phase the generator model can generate new images (Synthetic) by sampling the latent variables then decode to get synthetic images from each class.

3.4. CLASSIFIER MODEL: -

Here this section describes the classifier model used to increase the model efficiency. The classifier structure is represented in figure 3. The classifier model is assumed to be binary classifier that detects whether the testing image has tumour or not. The classifier model here used is Resnet-50. Figure .2. ResNet50 architecture

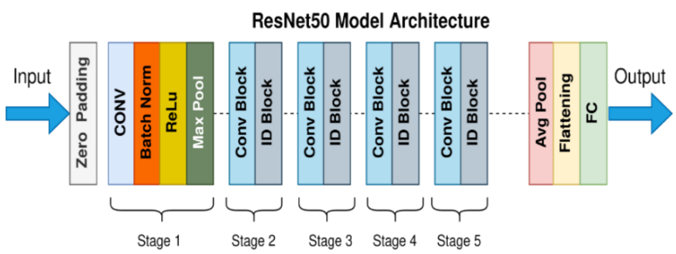


Figure .2. ResNet50 architecture

ResNet50 is a variant of ResNet model which has 48 Convolution layers along with 1 MaxPool and 1

Average Pool layer. It has 3.8 x 109 Floating points operations. After training data, the feature has been extracted as a model file and the final trained model file has been generated. When an input image is given for disease prediction, it will predict the presence of disease and we will check whether the data is accurate or not. Thus, this project helps in identifying the presence of brain tumour in a more efficient way, thus saving the life of the patient at the earliest.Type equation here.

3.5. DISCUSSION: -

This proposed Model consists of 2 different models of 2 different functions. The first model is Generator model and the second one is Classifier model. The Generator model is used to create more number of image samples for each class using small unbalanced dataset. The Classifier model only targets on classification. At first Generator model is trained to generate synthetic MRI images The generator model is trained individually from the classifier model. The original samples, synthetic samples both were used for training the classifier model. This framework is used for different detection, classification problems.

IV. EXPERIMENTS AND RESULTS

The separate training the different classes in dataset and images

Fig 3. Outputs for synthesis Yes images

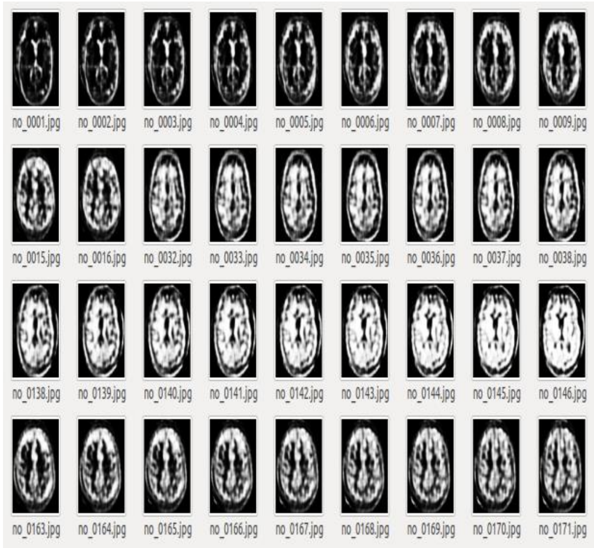
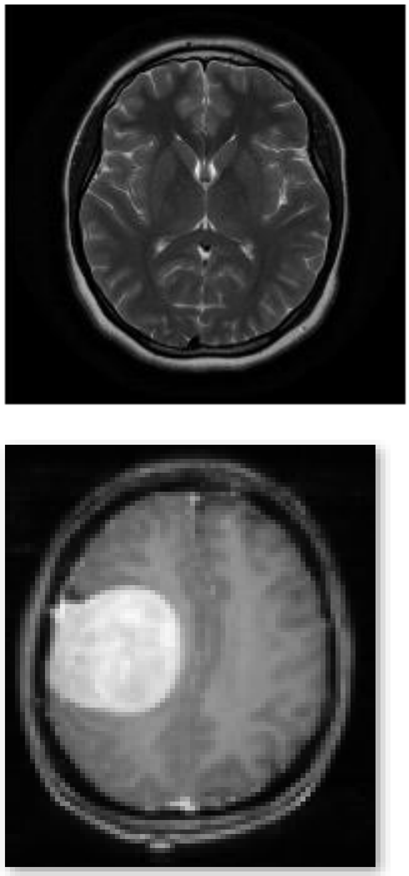


Fig 4. Outputs for synthesis no images



Label: NO Label: Yes

Fig 5. Classifier outputs

4.1. DATASET DESCRIPTION: -

Here used a small dataset of image samples typically 253 samples. This dataset is openly available in kaggle website and is used for classification. Here used 65% for training and 35% for testing.

4.2. PROPOSED FRAMEWORK :-

The proposed model has two networks. Generator network and classifier network. The pre-processed images were used to train the generator network. As the generator network was not capable of generating clear brain MRI images so, by increasing the number of iterations (training time) the generates clear images that typically resemble the clear Brain MRI images. Here generator network is used to convert small dataset to larger dataset of 1000 samples which contains 500 for each class. The newly generated dataset is used for training the classifier network for detection.

4.3.PERFORMANCE METRICS: -

There were several evaluation tools to assess a classifier among them some were used here. The parameters used here were Accuracy, Precision, Recall, F1-score and Kappa score.

ACCURACY:-

Accuracy is defined as the

$$\text{Accuracy}=\frac{t_p+t_n}{t_p+f_p+f_n+t_n}$$

PRECISION: -

Precision is defined as the

$$\text{Precision}=\frac{t_p}{t_p+f_p}$$

Recall: -

Recall is defined as the

$$\text{Recall}=\frac{t_p}{t_p+f_n}$$

F1-score: -

F1-score is defined as the

$$\text{F1-score}=\frac{2*(recall*precision)}{(recall+precision)}$$

Kappa score: -

Kappa score is defined as the

$$\text{Kappa score}=\frac{p_o-p_e}{1-p_e}$$

Note:- Accuracy and Precision are independent of each other.

4.4. Model Accuracy: -

In this section loss and detection accuracy for training and testing for classifier network. The detection accuracy for training and testing increases together and also the detection loss of training and testing decreases together which means the classifier model is not over-fit with training data. This is so because synthetic image samples helps in generalising the classifier.

CONFUSION MATRIX

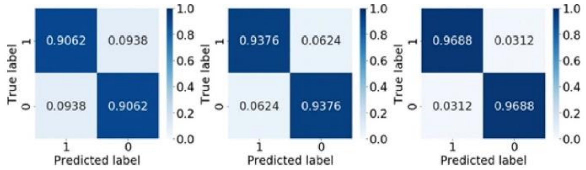
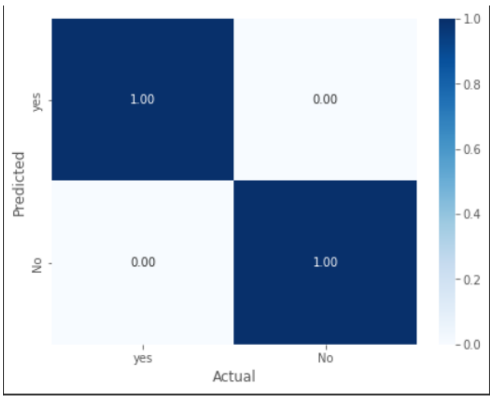


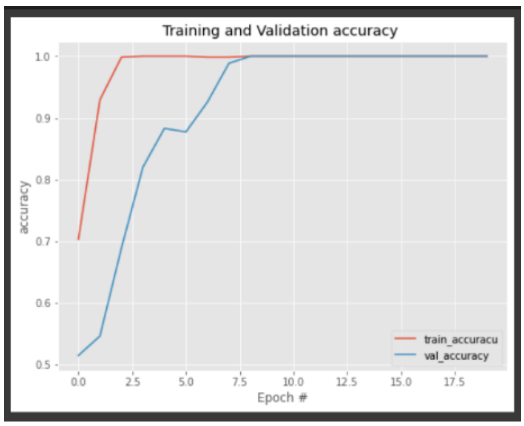
Fig.6. (a)CNN Method (b)Transfer Learning

(c)Existing framework



(d)Proposed framework

GRAPHS



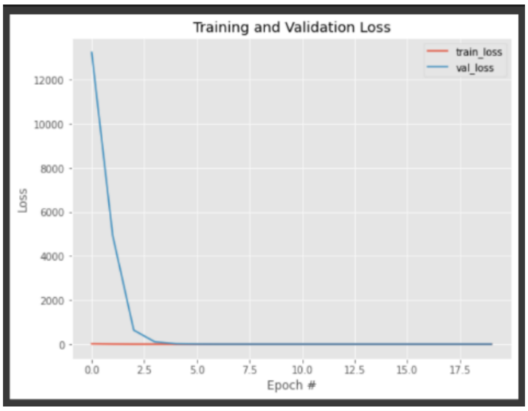


Fig.8. 65%training and 35% testing Accuracy and validation graphs.

4.5. COMPARISION WITH OTHER SYSTEMS

System	Accuracy	Precision	Recall	F1-score	Kappa score
CNN	90.62	90.62	90.62	90.62	Na
Transfer learning	93.75	93.75	93.75	93.75	Na
Existing framework	96.88	96.88	96.88	96.88	0.945
Proposed framework	99.71	100	99.45	99.45	0.994

4.6. TIME COMPARISION:-

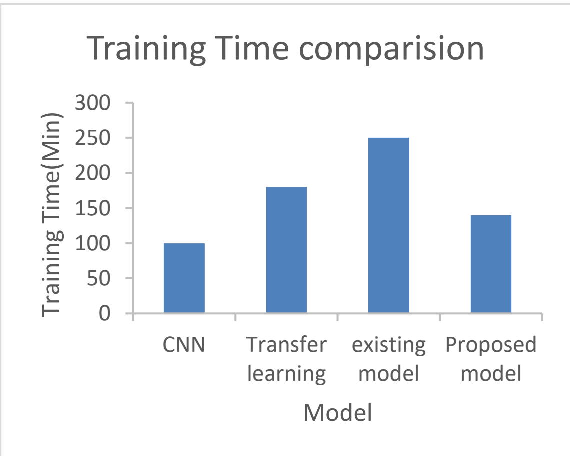


Fig.9. Time comparison with various models

V. CONCLUSION

A generalised framework for brain tumour detection and classification is developed in this paper. The proposed framework uses two deep models for different tasks, one is for converting small unbalanced dataset to large balanced one and other is a classifier model of Resnet-50 which is used to detect tumours in brain MRI images. The Proposed framework acquired a best performance of 99.4% in average of Accuracy, Precision, Recall, F1-score, Kappa scores.

VI. FUTURE SCOPE

We can extend this project further by taking different datasets for classification, and finding out the location of tumour in brain, its size and density can be further be included.

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