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Fast Regional Convolutional Neural Network Integrated with Multiclass Linear Support Vector Machine to Classify Brain Tumour from MRI Images.

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ABSTRACT:

Segmentation of brain tumour is the pivotal task in medical image processing. Manual segmentation of brain tumour is an ambitious task and also time-consuming process. Numerous Computer Aided Diagnosis (CAD) methods have been proposed in medical imaging applications. Recently, deep learning approaches have been used to magnify the performance of existing machine learning techniques. In this paper, localisation of brain tumour in MRI images based on deep learning mechanism is proposed. Convolutional Neural Network with Multiclass Linear SVM is used for brain tumour classification and Fast Regional Convolutional Neural Network is used to localise the brain tumour. First phase, consists of 5 layer CNN architecture is used for segmentation and feature extraction. MCLSVM classifier is used to classify brain disease into normal, edema, enhancing tumour, non-enhancing tumour and necrosis. Second phase, FRCNN model is proposed for localisation of brain tumour. The performance of localisation methods is quantified with the help of different evaluation metrics. Our proposed model approach 89.21% accuracy and 0.89 Dice Index score.

Keywords: *Convolutional Neural Networks, Multi Class Linear Support Vector Machine, Fast Regional Convolutional Neural network.*

1. Introduction

In clinical practice, medical imaging mainly Computed Tomography (CT) and Magnetic Resonance Images (MRI) has been used to determine the presence of a tumour in brain images. Numerous approaches have been made to segment the brain image automatically. Segmentation algorithm based on regional, texture and histogram thresholds are simple but lack accuracy. Nuclear Magnetic Resonance imaging is a clear and high resolution image of brain tumour [1].Current literature report that automatic computerized detection and diagnosis of the disease, based on medical image analysis could be in a good alternative. MICCAI is a conference held every year focusing on medical image computing and computer assisted intervention. Recently many methods detected to deep learning were presented in the conference. Brain tumour detection is an important task in medical image processing. Brain tumour is a serious disease in which an abnormal growth of tissue inside the brain leads to improper brain function [2]. The National Brain Tumour Foundation (NBTF) [3] reported that the number of people in developed countries who have died due to brain tumour has increased by 30% over the last three decades [4][5]. Therefore, evolving an automatic brain tumour diagnosis system that achieves high tumour detection and localization accuracies is a vital need. The main contribution of this research is based on proposed techniques. Hybridization of 5 layers CNN with MCSVM used for brain tumour detection and Fast R_CNN based localisation is used.

2. Medical image Segmentation

Medical image segmentation is the process of identifying organs or lesions from CT scans or MRI images. It gives crucial information about the shapes and volumes of these organs. Identification of pixels of organs or lesions from background medical images such as CT or MRI images is one of the most demanding tasks in medical image analysis [6]. The biggest complication with classifying and segmenting the MRI images with some neural networks lies in the number of images in the database. MRI images are assigned in different planes, sothe options of using all the available planes could enlarge the database. So it affects the classification outputs byover fitting.Hence, pre-processing is required before feeding the input images to the network [7][8]. In the 2000s, owing to hardware improvement, deep learning approaches came into the picture and started to demonstrate their considerable capabilities in image processing tasks. In the recent years, image segmentation based on deep learning techniques has received vast attention and it highlights the necessity of having a comprehensive review of it [9][10]. Three main types of NNs have been researched: Fully Connected NNs (FCNNs), Convolutional NNs (CNNs) and Recurrent NNs. (RNNs). Recent performances of deep learning methods, specifically Convolutional Neural Networks (CNNs) in object recognition and biological image segmentation challenges increased their favour among many researchers [11]. CNN automatically learn representative

complex features directly from the data itself. Due to this property, research on CNN based brain tumour segmentation mainly focuses on network architecture design rather than image processing to extract features [12].

2.1 MRI Images

MR images have multiple imaging file formats which describes how the data is organized in the image file and how it should be interpreted for correct loading and visualization. Typical medical image file formats may contain basic information about the patient or the patient's medical history like DICOM file format. Examples of typical file formats used in medical imaging are Analyze, NIfTI, MetaImage and DICOM [13].

2.2 Segmentation Criteria - Manual Segmentation Procedure

The protocols used by expert radiologists in segmenting the different tumour region are [14]. The manual segmentation of MRI images into edema, enhancing tumour, non-enhancing tumour and normal tissue was shown in figure 3.

i) Segmentation from T2 and FLAIR images sequences- Peritumoral Edema sub-region (ED).

- Segmentation from T1c and T1 sequences- Gross Tumour Core which includes enhancing and non-enhancing tumour structures.
- Segmentation by Thresholding T1C intensities in the Gross Tumour Core - Enhancing tumour core (ET) excluding the Necrotic Core (NCR)

ii) The Necrotic Core (NCR)-low intensity necrotic structures within the enhancing rim in T1c.

iii) Non-Enhancing Core (NER)-resultant part after the subtraction of the Enhancing Core and Necrotic Core from the Gross Tumour Core.The results of the manual segmentation by the experts using the different modalities can be summarized as follows:

i) The Whole tumour (Yellow) and is visible in FLAIR modality.

ii) The tumour core (red) and is visible in T2 modality.

iii) The enhancing core (blue) and necrotic core (green) are visible in T1c modality.

iv) The combined segmentation of the tumour structure: edema (yellow), non-enhancing core (red), necrotic core (green) and enhancing core (blue)

3. Related Work

In current scenario, deep learning based neural networks gaining their magnetism in the computer vision community. Majority of brain tumour researchers used BRATS database since it has all four modalities with ground truth and it also available in different forms such as BRATS 2013, BRATS 2015, BRATS 2017, and BRATS 2018. Different deep learning architectures are used by researchers for automatic segmentation and classification of brain tumours [15]. Mohammed et.al [16] proposed two pathways and cascaded architecture of CNN. In this, two architecture of CNN was used. The input is given to the two pathway architecture namely local path CNN and global path CNN. Finally, the outputs of these values were concatenated to get final output. Peter.et.al [17] presented CNN architecture that accepts 2D patches as its input. Intensity normalization and histogram modelling methods were used at pre-processing stage. They applied both normalization and bilinear interpolation at the hidden layer of CNN, which was ReLU and max pooling. Zhang et.al [18] proposed a method using CNN for the segmentation of three types of tissues namely White matter, Gray matter and Cerebro spinal fluid present in MRI images. The method used 2D patches of a single size from one plane in T-1 weighted; T-2 weighted as input images to CNN. De Brebisson et.al [19] presented a segmentation approach of adult T-1 weighted MR brain images in 134 regions as provided by the MICCAI challenge on multiatlas

Labelling. This method used multiple parallel networks 2D patches in orthogonal plane, a 3D patch and distance to a previous segmentation map. Zaka Ur Rehman et.al [20] proposed texture based localization of tumor from MRI by using machine learning approach. However, the above mentioned methods were all on the patch-wise methods. So this method performed the segmentation task which will result in some errors and need post processing. Thus, the computational time and post processing become a tedious process. Our main contribution of this work is to propose a hybridization of CNN, MCSVM and FR_CNN based deep learning system for brain tumor detection and localization from MRI data. This approach not only detect tumor accurately but also FR_CNN speed the localization process and the prediction efficiency.

Summary of brain tumor based on machine learning and deep learning methods given in Tab 1.

Table1 Summary of brain tumor based on machine learning and deep learning methods.

S. No	Authors	Database	Method
1	Coroso et al. [17]	20 cases of vivo brain tumors.	Affinity based segmentation method
2	Usman and Rajpoot [18]	MICCAI-BRATS 2013	Wavelet based and random forest classifier
3	Bauer et al.[16]	10 multispectral patient datasets	SVM with CRF
4	Mohammod et al.[11]	Brain Web data	N-cut graph segmentation
5	Zikic et.al[20]	BRATS 2013	3D CNN
6	Urban et al.[9]	BRATS 2013	3D CNN
7	Havaei et al.[21]	BRATS 2013	Cascaded CNN architecture
8	Davy et al.[22]	BRATS 2013	Two pathway CNN architecture
9	Peter et al [12].	BRATS 2013	2D CNN
10	Kamnitsas et al [23].	BRATS 2015	3D CNN with CRF

4. Deep learning in medical imaging

Neural networks are one of the powerful tools for image segmentation. The proposed system implement the automatic segmentation method based on CNN exploring small 3*3 kernels. The small size kernels help to design deeper architecture by using fewer numbers of weights in the network. The main particularity of deep learning is the nature of the considered candidate functions. The term deep is related to multiple compositions of functions.

The main contribution of this research is based on two proposed techniques.

i) Hybridization of CNN, MCLSVM and FR_CNN based deep learning system for brain tumour detection and localization from MRI.

- In the first phase MRI brain tumour are classified into normal and abnormal images using convolutional neural network.
- Combination of CNN and multi class linear SVM is used in brain tumour detection.
- In the second phase FR-CNN is used to localize the tumour.

5. Proposed approach

The proposed work consists of four modules.

a) Preprocessing module using edge detection and normalization

b) Feature extraction based on convolutional Neural Network

c) Classification of brain tumour images into normal and abnormal using MCLSVM

d) Localization of tumour images using FR_CNN.

Thus, hybridization of CNN, MCLSVM, and FR_CNN was employed for brain tumor classification and localization. The general flow diagram of segmentation and classification is shown in figure 1.The proposed work is shown in figure below figure 2.

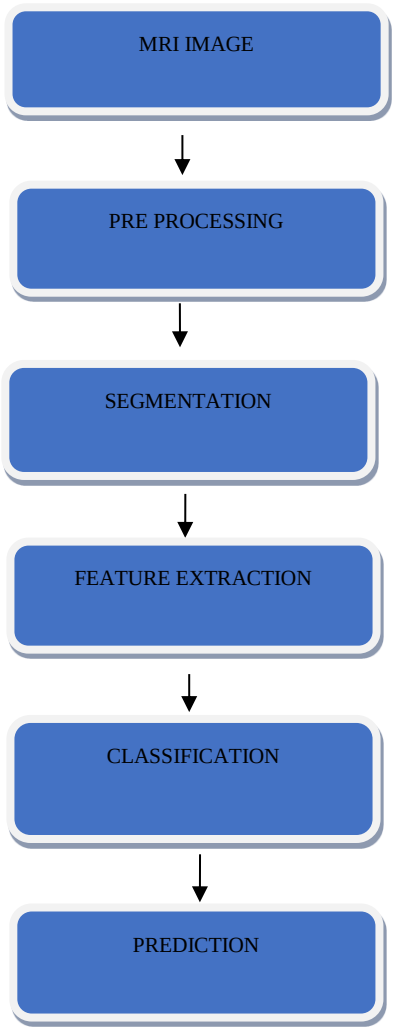


Fig 1.shows the general flow diagram for MRI image segmentation and classification.

5.2 Pre-processing stage

Due to intensity inhomogeneity in a magnetic field (or) small movements created by the patient during scanning, artifacts is produced in the input MRI images. Segmentation results also affected by the time bias are present in the scanning results. So the most challenging task is to remove artifacts in the input MRI images. The input MRI image is adjusted to 240*240 *3 RGB images, which is effective input to Binarizxation process. Binarization is performed for the input MRI resized images. After that, noise reduction is performed by Gaussian or median filter in order to standardize the pixel intensities. Apply normalisation to scale pixel values to 0-1. Then the input MRI images are provided to the trainable CNN in the feature extraction stage.

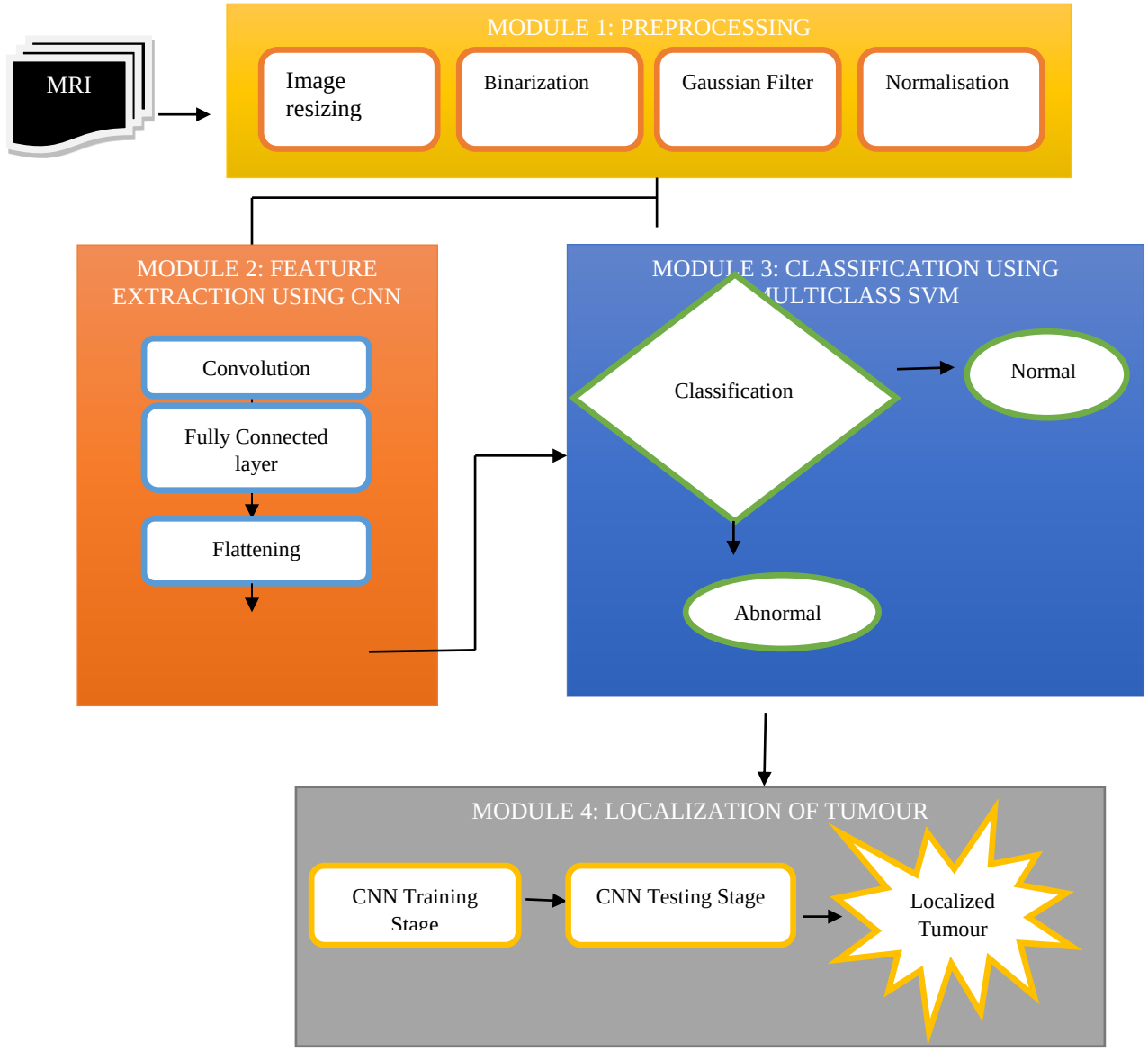


Fig Brain tumour classification and localization using deep learning mechanism

5.3 Feature Extraction using CNN

A CNN is branch of neural networks and consists of a stack of layers each performing a specific operation, e.g., convolution, pooling, loss calculation, etc [21][22]. Each intermediate layers receives other output of the previous layer as its input. The beginning layer is an input layer, which is directly connected to the number of pixels in the input image. The next sets of layers are convolutional layers that present the result of convolving certain number of filters with the input data and perform as a feature extractor. The filter commonly known as kernels, are of arbitrary sizes, defined by designers, and depending on the kernel size. Each neuron responds only to a specific area of the previous layer, called receptive field. The output of each convolutional layer is considered as an activation map, whichhighlights the effect of applying a specific filter on the input. Convolutional layers are usually followed by activation layers to apply non-linearity tothe activation maps. The next layer can be a pooling layer depending on the design and it helps to reduce the dimensionality of the convolutional output. There are some strategies in pooling operation such as max pooling and average pooling. Finally, high level abstractions are extracted by fully connected layers. The weights of neural connection and the kernels are continuously optimized during the procedure of a back propagation in the training phase [23]. The Hyper parameter value for CNN model is shown in Tab 2.

Table 2 Hyper parameter value for CNN model.

Stage	Hyperparameter	Value
Initialization	Bias	0
	Weights	Glorot_unifrom
Training	Learning rate	0.001
	beta_1	0.9
	beta_2	0.999
	epsilon	None
	decay	0.0
	amsgrad	False
	epoch	25
	batch_size	32
	steps_per_epoch	80

5.3.1 Model design

The input dataset was split in the following ways.

70% of data for training

15% data for testing

15% data for validation.

Proposed algorithm for the Working methodology:

- Load the input MRI images.
- The input MRI image is applied to convolution layer with 32 convolution filters.
- Then the pooling operation is performed for the (62*62*32) filters by max pooling layer to get a single column vector as output.
- Flatten the (31*31*32) max pooling layer output.
- Processing the single column vector by using dense layer with 128 nodes.
- ReLU activation function is used for final dense layer.
- Validation stage and performance measures.

The algorithm for CNN architecture is as follows.

General Algorithm for CNN

The algorithm for CNN architecture is as follows.

model=Sequential()

model.add(Conv2D(32, kernel_size=5, input shape=(28, 28, 1), activation = 'relu"))

model.add(Conv2D(32, kernel_size=5, activation = "relu"))

model.add(MaxPool2D(2, 2))

model.add(BatchNormalization())

model.add(Dropout(0.4))

*model.add(Conv2D(64, kernel_size=3, activation = "relu"))_*

*model.add(Conv2D(64, kernel_size=3, activation = "relu"))_*

model.add(Dropout(0.4))

model.add(Conv2D(128, kernel_size=5, activation = "relu"))

model.add(BatchNormalization())

model.add(Flatten())

model.add(Dense(256, activation = "relu"))

model.add(Dropout(0.4))

model.add(Dense(256, activation = "relu"))

model.add(Dropout(0.4))

model.add(Dense(10, activation = "softmax"))

The network architecture for the feature extraction process is shown in figure 3.

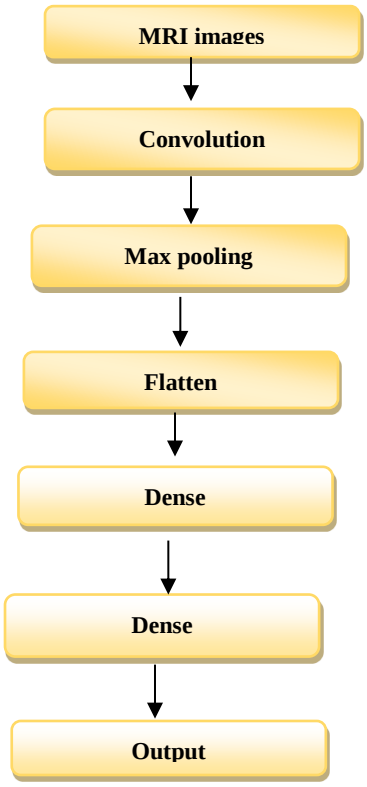


Fig 3. Network architecture for Feature extraction process using 5-layer CNN.

5.4 Classification suing MCLSVM

Multi class linear SVM based on one-versus-one approach. It is an extended version of binary SVM. It is used to classify more than two classes [24][25]. For all different combination of classes MCLSVM constructed different hyper planes with training a separate classifier, for each different pair of classes. In our work, MCLSVM is used to identify a tumour present in MRI image. It is used to classify five different types of tumour classes normal tissue, necrosis, edema, non-enhancing, enhancing tumours. The general pseudo code for MCLSVM is shown below.MCLSVM was implemented using the toolbox in python multisvm.py.

sklearn datasets import modules

load training and testing dataset

define kernel and kernel parameters

create two class SVM classifier

create multiclass SVM classifier (training)

set input data and labels

start training and set model

create multiclass SVM classifier (prediction)

set input data and model

start prediction and get labels.

5.5 Brain Tumour Localisation Phase

In the post processing stage we use bounding box algorithm to detect the tumour region from the segmented MRI image. The MRI images with the tumour bounding box are provided to the R-CNN block to train the network. In post processing, the properties of region in the tested image are measured and the most interested with the R-CNN is selected as tumour region.

5.5.1 Region based convolutional neural network

R-CNN offers high object detection and accuracy. The R-CNN methods train a CNN to classify the image into an object. It uses the log loss approach to fine tune the image regions to objects. Then, an SVM approach is applied to detect objects. R-CNN and Fast R-CNN approaches are used in the localisation phase.

In R-CNN model, the several proposed regions from an image were selected and then label their categories and bounding boxes. After that, CNN is used to perform forward computation to extract features from each proposed region. The features of each proposed region is used to predict their categories and bounding boxes. The general flow of RCNN model is shown in figure 4.

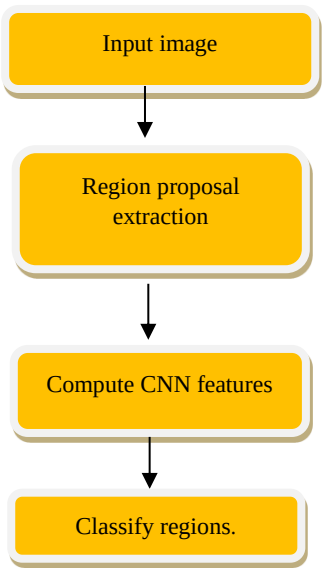


Fig 4. General flow of RCNN model.

Problems in RCNN: RCNN takes huge amount of time to train the network. It was based on selective search algorithm. The selective search algorithm is a fixed algorithm.

5.5.2 Fast Regional Convolutional Neural Network

(Fast R-CNN):

In fast RCNN the input image was feed into CNN to generate a convolutional feature map, instead of feeding region proposals to the CNN. The region of proposals were identified from the convolutional feature map and then wrapped into squares. The fixed size of the feature map was obtained by using ROI pooling layer before feeding into the fully connected layer. The class of the proposed region was predicted by using the activation function which obtained from the ROI feature vectors. The general flow diagram of FRCNN is shown in figure 5.

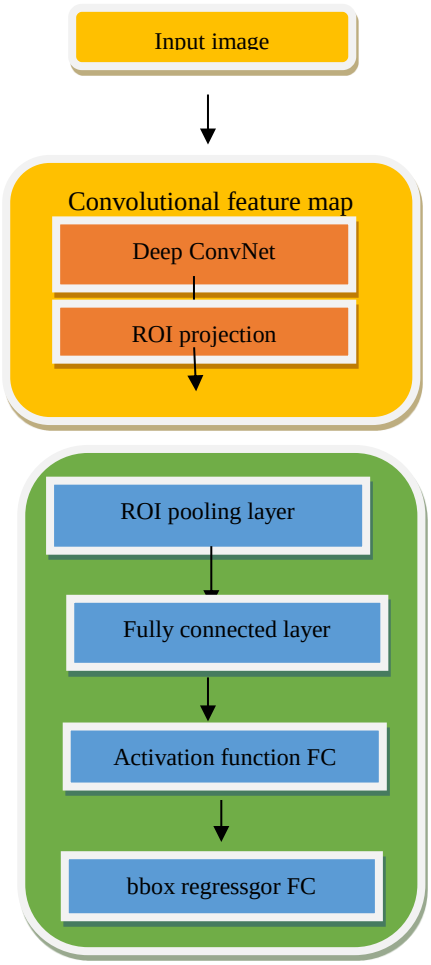


Fig 5.General flow of FRCNN model.

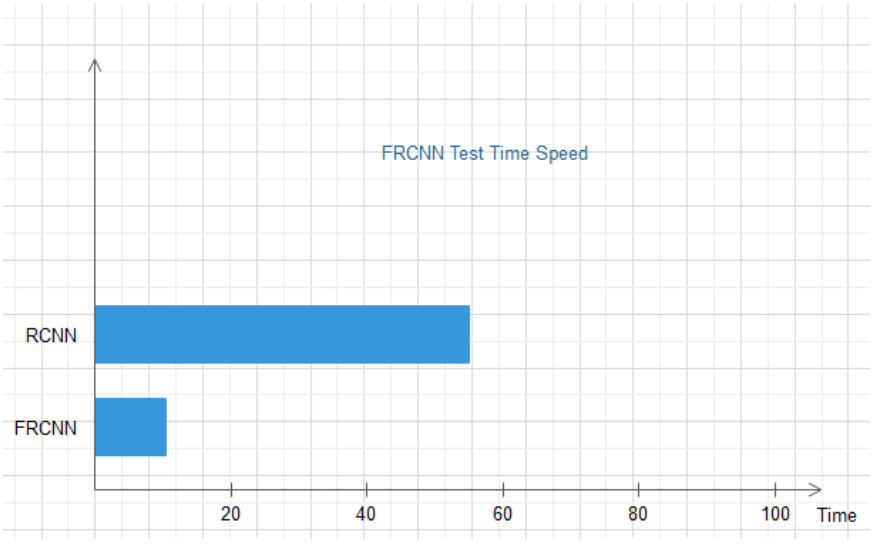


Fig 6. Comparison of test train time of RCNN and FRCNN algorithms.

6. Results and Discussion

The image database used for evaluating the tumour detection phase was extracted from the BRATS database, consisting two classes namely class 0 and class 1. In this database 480 MRIs, in which 253 images are normal and 227 images are abnormal. A set of features are extracted from these images for

each MRIs which was used to train MCLSVM. T-1 weighted and T-2 weighted MRI images were used. MCLSVM classified the brain tumour into five classes namely normal, edema, enhancing tumor, non-enhancing tumour, and necrosis.

6.1 Validation of the network

For experimental setup, the benchmark dataset was used to evaluate the performance of the network. A dataset of 804 MRI images extracted from BRATS database. From the images, 70% of images were used for R-CNN training, 15% of images were used for testing, and 15% images were used for validation**.**

6.2 Performance Evaluation Criteria:

The following standard metrics were used for the evaluation of this work sensitivity, which represents the proportion of actual positives that are correctly classified; specificity, which indicates the proportion of negatives that are correctly classified; and accuracy, which is the proportion of both true positives and negatives. The metrics were calculated based on the equations shown below.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

In addition to this, some other parameters were used for evaluating tumour detection of localisation phase. Dice Score are considered a common parameter for tumour localisationapproaches. The performance evaluation of MRI images is shown in graph below figure 7. Comparison of test train time of RCNN with FRCNN is shown in Fig 6.

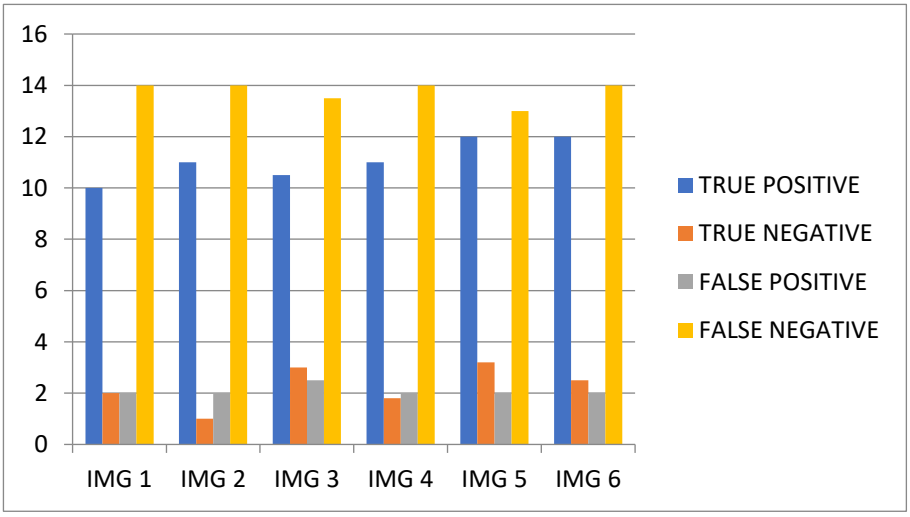


Fig 7. Simulation results of TP, TN, FP, and FN of sample MRI images.

6.3 Pre-processing results

Experiments were conducted for the dataset using Python with keras nad tensorflow libraries. The input MRI images from the dataset were used for the pre-processing purpose and their results shown in figure 8. The mean standard deviation and variance values are computed for the pre-processed images is shown in figure 9.

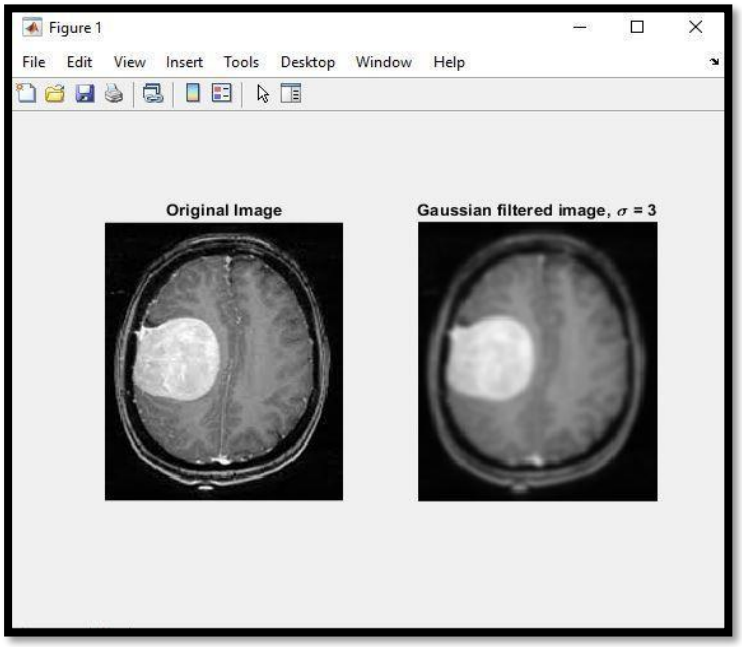


Fig 8.Gaussian filtered image

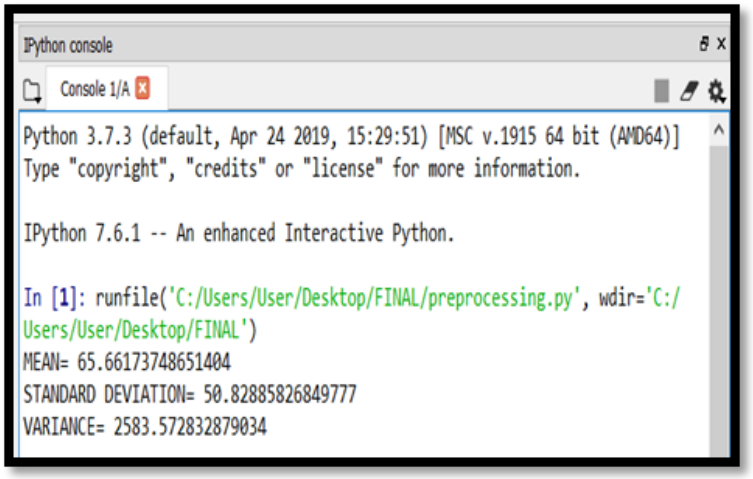


Fig 9. Computation of statistical values for Gaussian filtered image

6.4 Tumour detection accuracy analysis

The performance of CNN is measured in every network layer for identifying the optimum number of network layers and shortest feature extraction time to achieve highest accuracy. In this 5 layer CNN with keras is used to build the network architecture. A sample from the dataset for which the matplotlib is used. In this 5conv2d layer, 2maxpool2d, 3 layers of batch normalisation and 4 layers of dropout was used. And flatten () layer was used to get the image dimensionality down to 1D and add 2 dense Fully connected layer on top to process 1D image vectors. ReLU activation function was used to improve the neural network by speeding up the training process. The CNN model is compiled using categorical_crossentropy as the loss function and Adam as the optimizer for this model. The network architecture 5 layer CNN with keras was constructed using Python is shown in figure 10. The CNN architecture is used to train the datasets is shown in figure 11. The network layer of CNN is shown in Table 3. The training of the network with epochs is shown in figure 12.

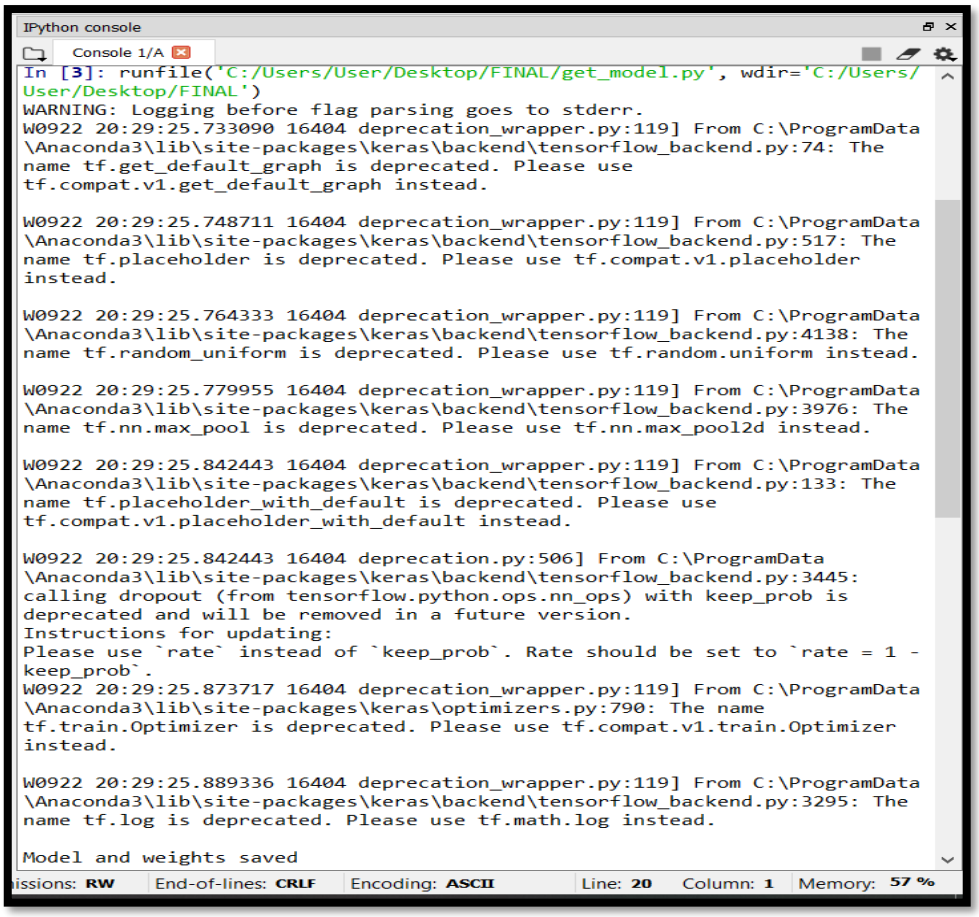


Fig 10. shows how the CNN architecture is constructed using keras.

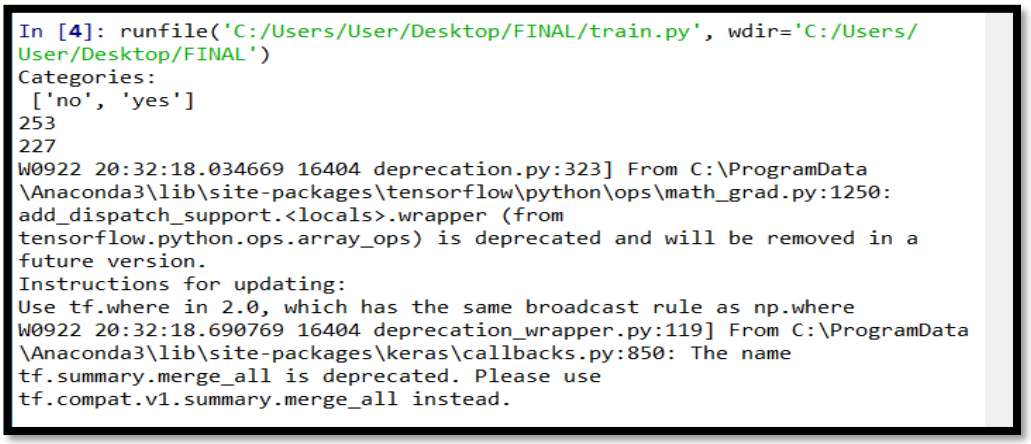


Fig 11. shows the training of the network using the CNN architecture.

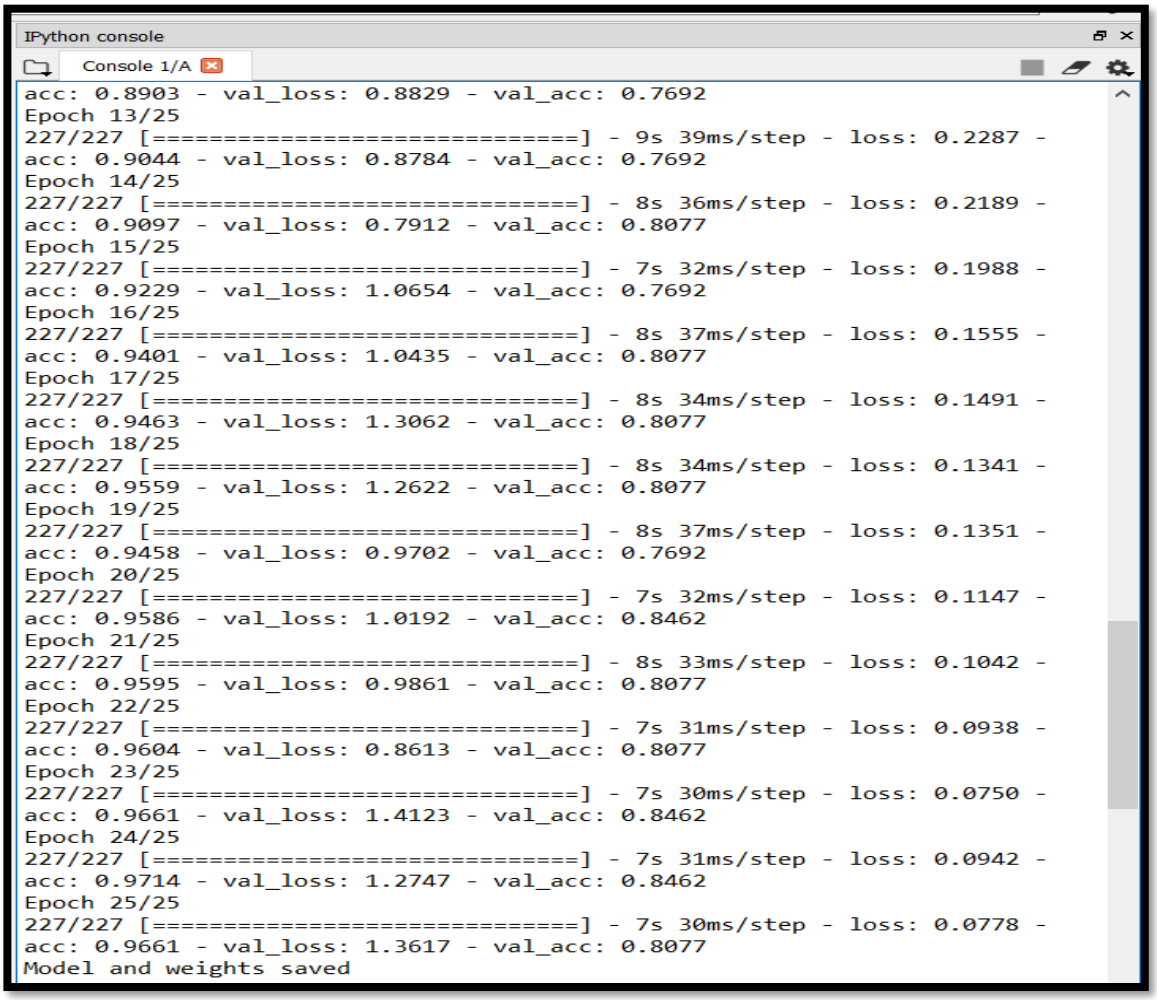


Figure 12 shows the training of the network with epochs =25

The network size has been optimized to give the best performance in learning phase. This network size has been fixed with the validation and testing phases to generalize the CNN model for all data samples. The proposed CNN model achieved 89.61% accuracy, while the other classical methods achieved 85%. A short comparison between the performance of previous classical method and the newly proposed CNN model using the same datasets is shown in table 3.

Methods	Accuracy	Datasets
CNN+KNN	83.71%	RIDER Neuro
DNN	86.88%	BraTS 2015
Proposed	89.61%	BraTS 2013

Table 3 Comparison of proposed CNN based brain tumour detection approach against some of the other methods.

Classification	Accuracy	Specificity	Precision	Recall	Dice Score
KNN	84.31%	0.457	0.81	0.83	0.80
DNN	88.88%	0.342	0.83	0.84	0.86
LOGISTIC REGRESSION	85.50%	0.545	0.85	0.83	0.92
MUTLILAYER PERCEPTRON	75.43%	0.7	1	1	0.93
PROPOSED	89.30%	0.432	0.89	0.88	0.89

Table 4. Comparison of classifier MCLSVM with other methods.

From the table 4, MCLSVM gives the most prominent result and it is 89.30% accuracy. From other performance metrics, it is also concluded that MCLSVM obtained the pre-eminent results in terms of accuracy, sensitivity, precision, recall, and Dice score. The performance analysis of classifier methods compared with our proposed model is shown in figure 13.

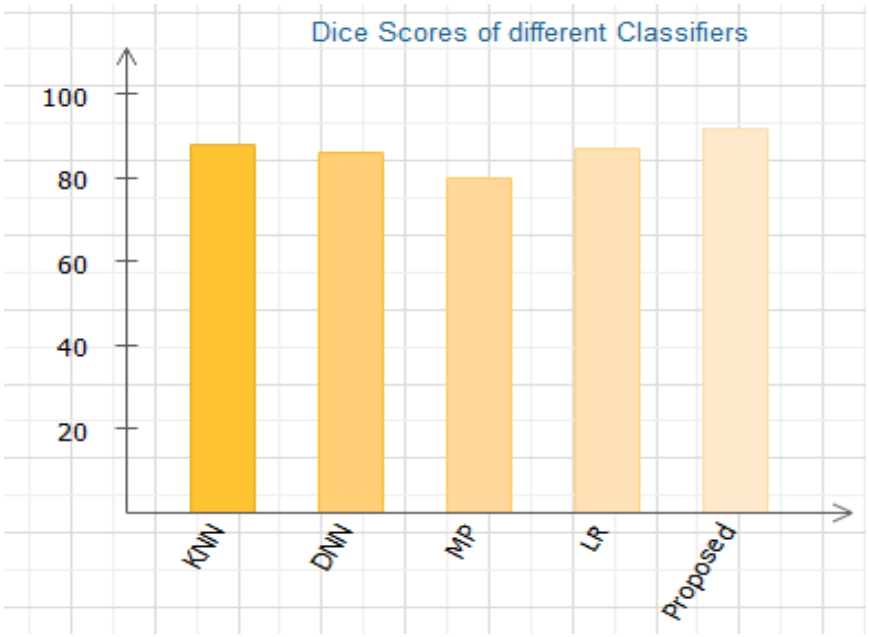


Fig 13.shows performance analysis of classifier methods compared with our proposed model.

6.5 Tumour localisation accuracy analysis

In this phase, fast region based Convolutionl neural network and region based convolutional neural networks were implemented to localize the tumour region in the MRI images. The performance analysis of the developed localisation using R-CNN based method compared with the proposed Fast R-CNN method is shown in table 5.

Method	Sensitivity	Dice
R-CNN	85.91	0.86
FR-CNN	89.31	0.89

Table 5 shows the performance analysis of the developed method is better than other methods.

It is clear that the proposed system is superior in terms of the network size, sensitivity and Dice metrics. A sample of visual results from the MRI database was used in the localisation phase of the experimental work is shown in figure 15. The performance analysis of Dice Score for the proposed method is shown in figure 14.

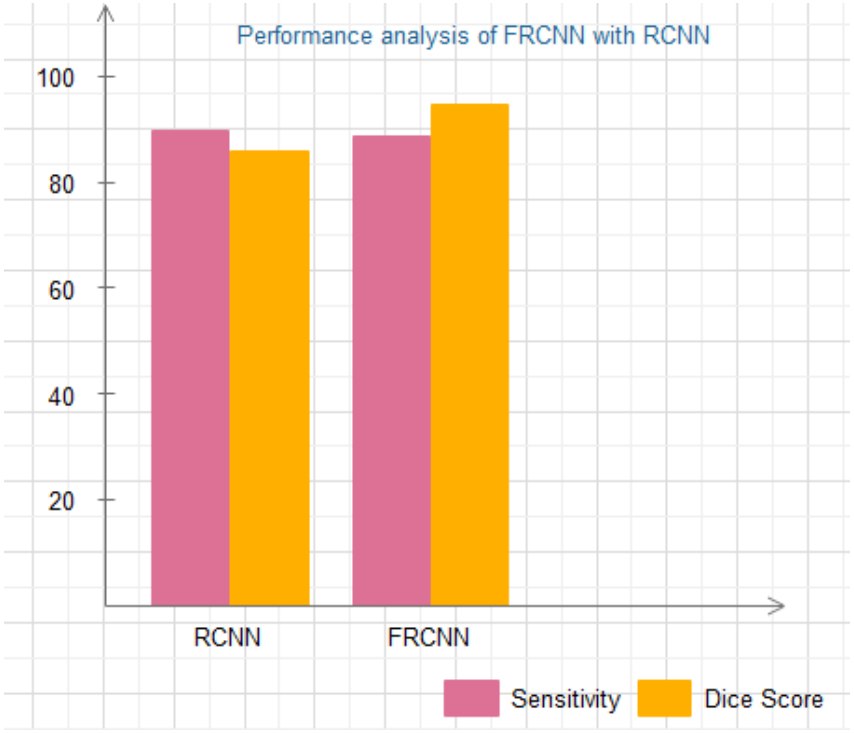


Fig14. shows performance analysis of Dice Score for the proposed method

```
In [6]: runfile('C:/Users/User/Desktop/FINAL/predict.py', args='C:/Users/
User/Desktop/FINAL/Data/input/Y1.jpg', wdir='C:/Users/User/Desktop/FINAL')
Reloaded modules: get_dataset
It is  Affected !
non-enhancing
```

Fig 15. shows the prediction of brain disease using MCLSVM method.

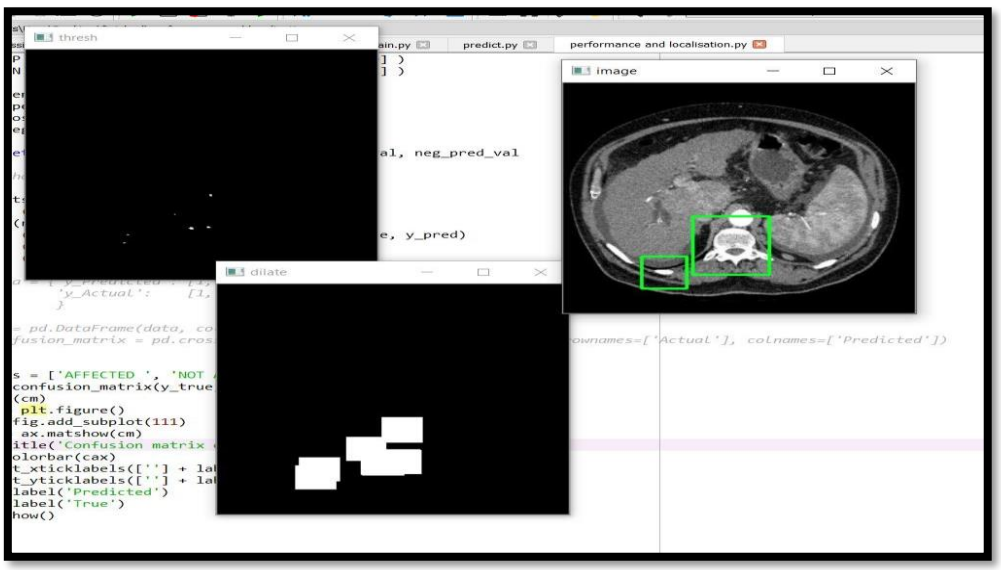


Figure 16 shows the tumour localisation using FR-CNN method.

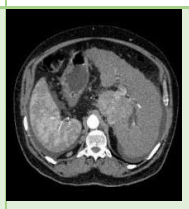
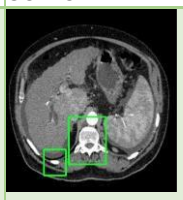
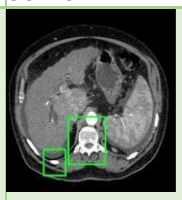
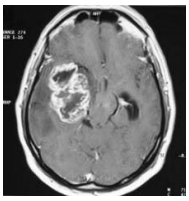
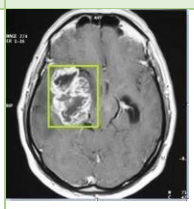
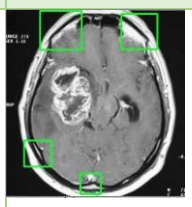
TEST CASE	INPUT	EXPECTED OUTPUT	ACTUAL OUTPUT	RESULTS
FRCNN				**Test passed**
RCNN				**Test Failed**

Figure 17 shows the tumour localisation using FRCNN shows superior performance when compared with RCNN method.

The tumour localization using FRCNN method is shown in Fig 16. The tumour localisation using FRCNN shows superior performance when compared with RCNN method is shown in Fig 17.The graph below depicts the training and validated accuracy of our model is shown in figure 22. It was calculated by the keras callback function. Different number of epochs were used for this model and observed that the training and validation accuracy achieved the maximum with number of epochs 25. Figure 21 shows the confusion matrix of the classifier using MCLSVM method.

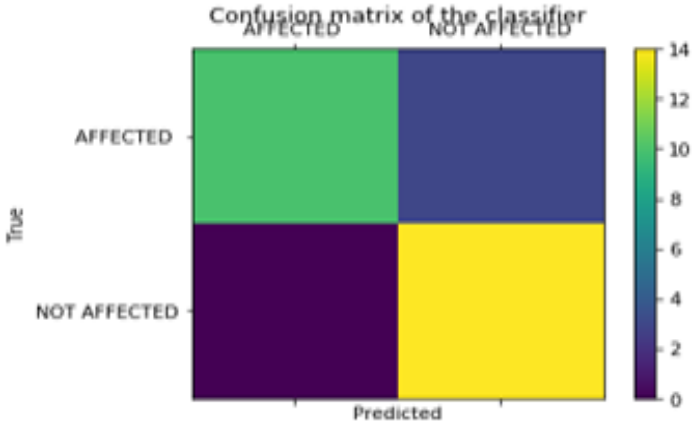


Fig 18. Confusion matrix of the MCLSVM classifier.

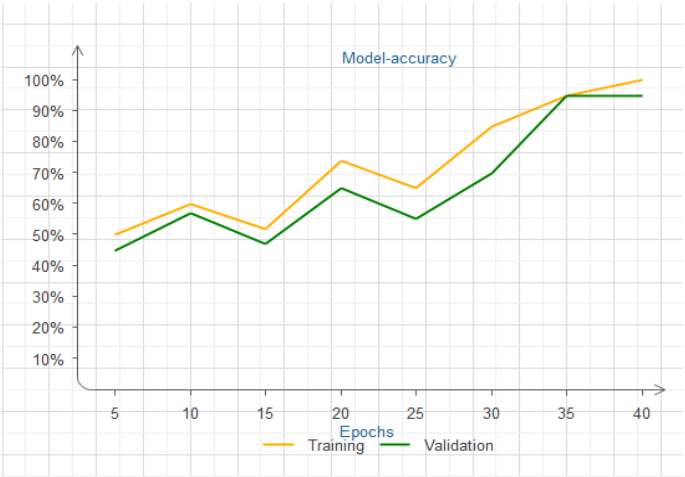


Fig 19.Shows the training and validated accuracy of our model.

Conclusion:

Segmentation of brain tumour plays an important role in diagnostic purposes. In this paper, we present an automatic framework for prediction and localisation of brain tumour in MRI images. First, CNN architecture is used for segmentation and feature extraction. Then multi class linear SVM is used for classification of brain tumour. The ability of the classifier is defined by the accuracy with which it's discriminated between healthy and diseased states. Localisation of brain tumour is done by Fast Regional CNN. The performance of localisation was quantified by comparing our model with RCNN model through the calculation of testing and training time. It is clear that the proposed system is superior to the other in terms of the network size, sensitivity, and specificity and Dice index. The accomplished results proved the superiority of the proposed method for brain tumour detection and classification. The performance measures validate and demonstrate the suitability of the proposed classifier in identifying different types of brain tumours considered in this study. In the future, we will explore different network architectures and training strategies to improve our results.

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Conflicts of Interests: The authors declare that they have no conflicts of interest to report regarding the present study.

References:

[1] Tiwari, Shilpa Srivastara, Millie Pant, "Brain tumor segmentation from magnetic resonance images: Review of selected methods from 2014 to 2019, *Pattern Recognition Letters*, vol.131, pp 224-260, March 2020.

[2] Mohammed Hesam Hesamian, Wenjing Jia, Paul Kennedy *et.al*, "Deep learning techniques for medical image segmentation: Achievements and Challenges", *Journal of Digital Imaging*, Vol.32, pp.582-596, 2019.

[3] Abien Fred Agarap , "A Neural network architecture combining gated recurrent unit (GRU) and support vector machine (SVM) for intrusion detection in network traffic data,"*ICMLC 2018: Proceedings of the 2018 10th International Conference on Machine Learning and Computing*, pp. 26–30, Feb 2018.

[4] Yang Deng, Yao Sun, Yong pei Zhu, Mingwang Zhu, weittan *et al*., "A strategy of mri brain tissue images' suggestive annotation based on modified u-net," C*omputer ScienceArXiv,* vol. abs/1807.07510, 2018.

[5] Z. Akkus, A. Galimzianova, A. Hoogi, D. L. Rubin, and B. J. Erickson, "deep learning for brain mri segmentation: state of the art and future directions," *Journal of digital imaging*, vol. 30, no. 4, pp. 449–459, 2017.

[6] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in mri images," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1240–1251,2016.

[7] D.N. Louis, A. Perry, G. Reifenberger, A. Von Deimling, D. FigarellaBranger *et al*., "The 2016 world health organization classification of tumors of the central nervous system: a summary," *Acta neuropathologica*, vol. 131, no. 6, pp. 803–820, June 2016.

[8] S. Bauer, R. Wiest, L. P. Nolte, and M. Reyes, "A survey of mri-based medical image analysis for brain tumor studies," *Physics in Medicine & Biology*, vol. 58, no. 13, pp. R97–R129, 2013.

[9] D. S. Marcus, A. F. Fotenos, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open access series of imaging studies: longitudinal mri data in nondemented and demented older adults," *Journal of cognitive neuroscience*, vol. 22, no. 12, pp. 2677–2684, 2010.

[10] P Kleihues, PC Burger and BW Scheithauer, "The new who classification of brain tumors," *Brain Pathology*, vol. 3, no. 3, pp. 255-268, 1993.

[11] K. Usman and K. Rajpoot, "Brain tumor classification from multi-modality mri using wavelets and machine learning," *Pattern Analysis and Applications*, vol. 20, no. 3, pp. 871–881, 2017.

[12] Liya Zhao and Kebin Jia, "Multiscale cnns for brain tumor segmentation and diagnosis," *Computational and Mathematical Methods in Medicine*, vol. 2016, pp. 7, 2016.

[13] S. Valverde, M. Cabezas, E. Roura, S. Gonzalez, D. Pareto *et al*., "Improving automated multiple sclerosis lesion segmentation with a cascaded 3d convolutional neural network approach," *NeuroImage*, vol. 155, pp. 159–168, 2017.

[14] K. Van Leemput, F. Maes, D. Vandermeulen, and P. Suetens, "Automated model-based tissue classification of mri images of the brain," *IEEE transactions on medical imaging*, vol. 18, no. 10, pp. 897–908, 1999.

[15] J. Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy *et.al*., "Recent advances in convolutional neural networks," *Pattern Recognition*, vol. 77, pp. 354–377, 2018.

[16] H.Mohammad,A.Davy,D.Warde-Farley, A. Biard, A. Courville, Y. Bengio *et al*., "Brain tumor segmentation with deep neural networks", *Medical Image Analysis*, vol. 35, pp. 18-31, 2017.

[17] D. Peter, M.D. Chang, "Fully convolutional neural networks with hyper local features for brain tumor segmentation", *Springer International Publishing AG, part of Springer Nature*, pp. 298-308, 2018.

[18] Zhenglun Kong , Ting Li , Junyi Luo,3 and Shengpu Xu, "Automatic tissue image segmentation based on image processing and deep learning," *Journal of Healthcare Engineering*, vol. 1, Article ID 2912458, pp. 1-10, 2019.

[19]Alexandre de Br´ebisson1 and Giovanni Montana, "Deep neural networks for anatomical brain segmentation,"*Computer Vision and Pattern Recognition, ArXiv: 1502.02445v1 [cs.CV]*, Feb 2015.

[20] Zaka Ur Rehman, M Sultan Zia,Gridhar Reddy Bojja, Muhammed Yoqub, Feng Jinchao *et al*., " Texture based localization of brain tumor from mri images by using machine learning approach," *Medical Hypotheses,* Vol. 141, pp. 110665, August 2020.

[21] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Image net classification with deep convolutional neural networks,"*Communications of the ACM*, vol. 60, pp. 84-90, 2012.

[22] K Mohana Priya, S Kavitha and B Bharathi, "Brain tumor types and grades classification based on statistical feature set using support vector machine", *IEEE 10th International Conference on Intelligent Systems and Control (ISCO)*, Coimbatore, India, November**,** pp. 1-8, 2016.

[23] D. Zikic, B. Glocker, E. Konukoglu *et al*., "Decision forests for tissue-specific segmentation of high-grade gliomas in multi-channel mr," *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2012, 15th International\Conference,* Springer, Berlin , Heidelberg, vol. 7512, 2012.

[24] J. J. Corso, E. Sharon, S. Dube, S. El-Saden, U. Sinha *et al*., "Efficient multilevel brain tumor segmentation with integrated bayesian model classification," *IEEE Transactions on Medical Imaging*, vol. 27, no. 5, pp. 629–640, 2008.

[25] Yichan Tang, "Deep learning using Support Vector Machines", International Conference on ML, Feb 2015.

Appendix A

In this appendix, we provide the information about the database and image processing toolbox used in this work. The dataset used in this work collected from various sources. The sources are given below.

https://www.kaggle.com/mateuszbuda/lgg-mri-segmentation.

https://nac.spl.harvard.edu/downloads.

https://www.med.upenn.edu/cbica/brats2020/data.html.

Appendix B

Various toolbox are utilized in this work. It can be found on

https://anaconda.org/anaconda/python.

https://in.mathworks.com/help/deeplearning/ug/deep-learning-in-matlab.html.

https://www.kdnuggets.com/2020/03/brain-tumor-detection-mask-r-cnn.html.