

Classification Comparative Analysis for Detection of Brain Tumor Using Neural Network, Logistic Regression & KNN Classifier with VGG19 Convolution Neural Network Feature Extraction

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doi: <https://doi.org/10.21467/proceedings.114.6>

Abstract

In recent years due to advancements in digital imaging machine learning techniques are used in medical image analysis for the prognosis and diagnosis of various abnormalities in the human body. Various Machine learning algorithms, convolution and deep neural networks are used for classification, detection and prediction of various brain tumors. The proposed approach is a different comparative classification analysis approach which is based on three different classification namely KNN classifier, Logistic regression & neural network as classifier. It is based on a deep learning feature extraction technique using VGG19. This VGG 19-layer image recognition model trained on Imagenet. Generally, MRI data sequences are analyzed in terms of different modalities and every modality contains rich tissue information. So, feature extraction from MRI sequences is very important task for brain tumor classification. Our approach demonstrated fair classification on BRATS Benchmarks 2018 data set with different modalities and sizes of images, results are without any human annotations. Based on selected classifiers all the classifiers gives accuracy above 90%. It is good compared to other state of art methods.

Keywords: MRI, images, Brain tumor segmentation, KNN, Neural network Logistic regression machine learning, VGG19.

1 Introduction

Most challenging medical field now a days using automated machine learning based classification of various types body images like CT Scan MRI Ultrasound images for accurate study of abnormalities, cancers & cysts diagnosis. In this type of studies researchers and professionals take help of various types of classifiers and these classifiers employs different types of features like morphological features such as area, height, width perimeter and many more. Most life threatening disease is brain tumor. Brain tumours are abnormal masses in or on the brain. It is uncontrolled cell proliferation growth of a cell as tumour. It may occur as a result of, a failure of the normal pattern of cell death, or both. Brain tumours can be either primary or secondary. Each of these tumours has unique biological, radiographical, and clinical characteristics that dictate, in part, their management. Malignant tumours generally grow fast and can spread to tissues in close proximity. Malignancy mostly referred to cancer. Benign tumours do not spread and grow slowly. Even though benign tumours are serious and can be life threatening, growing in a confined limited space, a benign tumour can exert pressure on the brain and compromise its function. The location of the tumour is key to diagnosis. Just use of MRI cannot reliably differentiate between the different types of tumours on the basis of imaging. The information of tumour location can be very helpful for prediction of the exact histology of the tumours.

MRI has been accepted as the major diagnostic modality for the brain tumor analysis. Comparing with CT scan MRI are more sensitive for brain tumours. MRI used for both for detection of tumours as well as in showing more completely the extent of the tumour spread either residual or recurrent disease.



Multi-planar imaging used majorly for superior tumour localization, rather than increasing the detection rate of lesions. MRI significantly provides information about gross pathology and tissue characterization.

Although use of automated algorithms for classification of brain tumors using MRI imaging like T1 weighted T2 weighted FLAIR still there are few image modalities wise differences are there and segmentation tasks changes with imaging types there is need of comparative study of classification so we proposed approach in this paper. It is a different comparative classification analysis approach based on three different classification namely KNN classifier, Logistic regression & neural network based on deep learning feature extraction technique using VGG19 19 layer image recognition model trained on Imagenet. Since MRI data sequences different in terms of modalities but every modality contains rich tissue information so feature extraction is very important task for classification. Our approach demonstrated fair classification on BRATS Benchmarks 2018 data set, results are without any human annotations. Based on selected classifiers all the classifiers gives accuracy above 90% comparable to with other state of art methods.

2 Related Work

In this medical image analysis area lot of work is in progress for detection prediction of life threatening tumors. Recently many machine learning deep learning, convolutional neural network based automatic tumor segmentation methods presented in different research articles. This related work point presents review of few deep learning and CNN based approaches.

In paper [1] Author Neelum Noreen et al. (2020) done the identification of brain tumor using deep learning models. In this paper they described two different methods. Softmax classifier used to classify the brain tumor based on the features extracted from pretrained DensNet Block. Pre-trained Inception-v3 model used for feature extraction and these concatenated features then used for the classification of brain tumors using softmax. Publically available three-class dataset used for brain tumor evaluation experiments. Comparing with the recent research methods for brain tumor classification author claim that the ensemble method using DensNet201 pre-trained model Inception-v3 outperformed. They claimed method produced 99.51% testing accuracy in detection of brain tumor with highest performance.

In [2], Mohamed A. Naser and M. J amal Deen (2020) in their research paper illustrates transfer learning models and use of deep learning for MRI images. It gives exact automatic grading of LGG brain tumors with segmentation and detection. Full automation is achieved by the use of pipeline of MRI images. It allows simultaneous grading and segmentation of the brain tumors. Author claims that this method shows a promising results as a non-invasive tool for tumors characterization in LGG.

In [3] Jakub Nalepa a,b (2019) for diagnosis and grading of brain tumors dynamic contrast-enhanced magnetic resonance imaging discussed. Fully-automated, end-to-end system DCE-MRI used for analysis of brain tumors. Pharmacokinetic modeling fitting error is decreased by using cubic model of the vascular input function. Author claims that an extensive experimental study and statistical tests carried out which shows state-of-the-art results using single GPU.

In [4] Ambeshwar Kumar a (2019) Author studied an efficient WCFS-IBMDNL technique for brain tumors diagnosis with minimal FAR. WC-FS used for medical feature detection and the IBMDNN used as classifier.

In [5] Authors discussed radiomic features and an ensemble learning method for brain cancer detection. In [6] the paper using transfer learning Brain tumor classification explained by author. In [7] paper author explained use of deep convolutional neural network for brain tumor detection with transfer learning. In [8] paper with neutrosophic expert maximum fuzzy sure entropy and convolutional neural network brain tumor detection is done by authors. In [9] paper authors used deep learning features fusion of hand crafted features and done brain tumor detection. In [10] authors demonstrated brain tumor detection using statistical and

machine learning method. In [11] authors implemented deep learning based enhanced tumor segmentation approach for MRI brain images. In [12] authors implemented classification using deep learning neural networks for brain tumors. In [13] By using machine learning techniques authors done detection and classification of LGG and HGG brain tumor. In [14] authors demonstrated by using extensive data augmentation and deep CNN techniques multi-grade brain tumor classification. In [15] authors took review of Brain tumor segmentation techniques and various classifications from MRI Images

3 Proposed Approach Technologies and Flow

The proposed work flow consists of implementation of comparison of three classifiers based on features extracted using VGG19 layer network image recognition trained on ImageNet 253 image instances are used two categories images with tumor & without tumor from which 4096 features extracted from VGG19 target with 2 values with 5 meta attributes. These features then given to logistic regression, knn classifier & neural network for classification of normal brain images or brain tumor images. BRATS 2018 data used for experimentation. Images are classed as Normal (No tumor) & Yes (Brain tumor) with these three classifiers. After deep inception training tests score F1 Score, AUC, Classification accuracy compared modelwise in comparison F1 score table & Depending on 5, 10 & 20 crossvalidation results plotted along with confusion matrix.

- i) VGG 19 Net: VGG19 Network architecture used in this work for feature extraction and extracted features then used in various classifiers for experimental results calculations and comparisons. Researchers at Visual Graphics Group at Oxford introduces VGG network (hence the name is VGG). VGG network is pyramidal shape network, where the top layers are deep and bottom layers which are closer to the image are wide.
- ii) Logistic Regression : Logistic regression is most popular predictive classification algorithm it works based on probability. Here as our classification is based on only two categories of images we have used lasso logistic regression for our tumorous and non-tumorous images it is used.
- iii) Neural networks: Neural networks are also used as general classifiers with activation functions like Relu and optimizers like adam. In this program also we used simple neural network with adam optimizers for classification based on features.
- iv) KNN Classifier: K-nearest neighbor is widely used classifier which is used to classify groups based on objects close to test value. In this work we have used Euclidean distance measure is used for classification of tumorous images based on features.

4 Experimental Results

In BRATS 2018 benchmark data set there are four different types of images T1, T1-c, T2 & FLAIR. In total 253 images with different sizes and intensities divides in two categories. Images with brain tumors labeled and named as 'yes' and normal images without brain tumor labeled and named as 'no'. For deep feature extraction 70% of images used as training data to VGG 19 deep 19-layer network. 30 % images used for testing results. Experimentation done for all three classifiers for 5, 10, 20 cross validation and then results are compared with charts. Sample images with different modalities with difference in size & intensities are shown in figures. Figure. 1 Shows Input training images with brain tumor labeled and named yes. Figure. 2 Shows Input training images without brain tumor labeled and named as no.

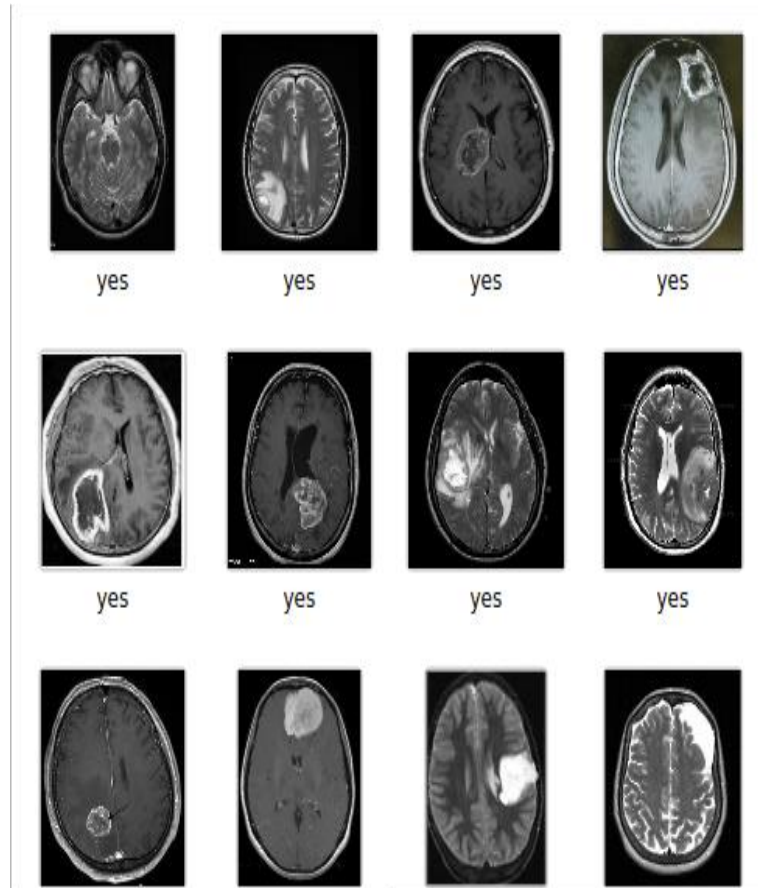


Figure. 1 Data set Images

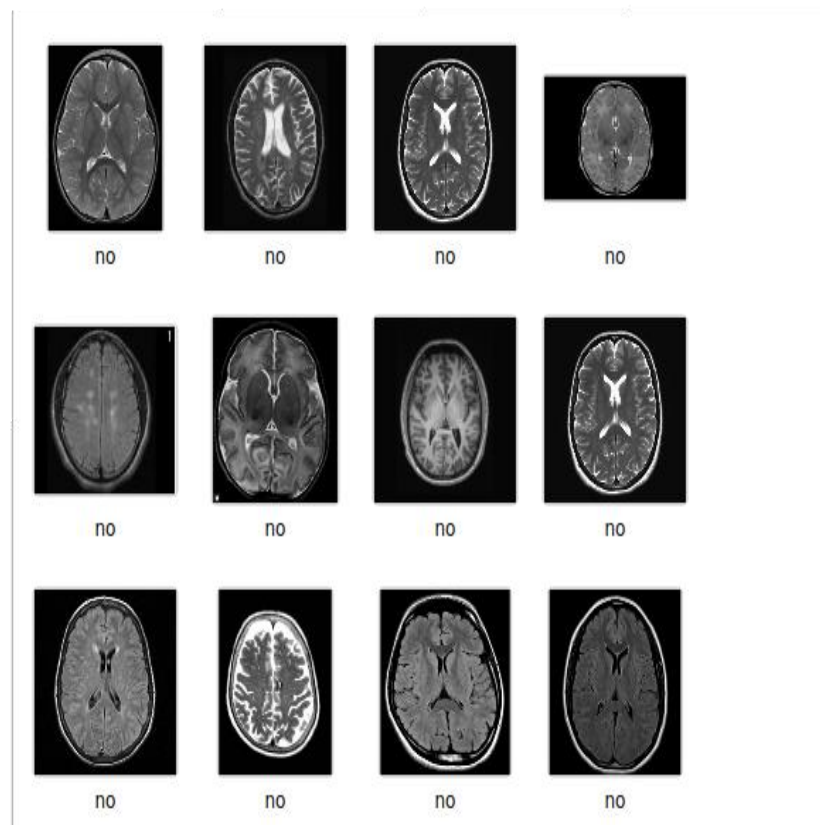


Figure. 2 Input Normal images without tumor

5 Classification Accuracy

With Any machine learning method or deep learning or convolution network classification accuracy is measured in terms of AUC, Precision F1 score & Recall rate. So in this point results are compared with three classification methods.

Table I represents the comparison of the implemented method with different cross fold validations 5,10,20 for logistic regression, neural network and KNN networks. With this chart we understand that logistic regression and neural network gives best classification accuracy even precision and recall is best for 20-fold cross validation.

TABLE I Comparison with different cross validation

| Cross Validation 20 | | | | | | |
|---------------------|---------------------|-------|-------|-------|-----------|--------|
| 1 | Model | AUC | CA | F1 | Precision | Recall |
| | KNN | 0.918 | 0.870 | 0.870 | 0.872 | 0.870 |
| | Neural Network | 0.936 | 0.881 | 0.882 | 0.886 | 0.881 |
| | Logistic Regression | 0.950 | 0.913 | 0.913 | 0.913 | 0.913 |
| Cross Validation 10 | | | | | | |
| 2 | Model | AUC | CA | F1 | Precision | Recall |
| | KNN | 0.911 | 0.858 | 0.858 | 0.859 | 0.858 |
| | Neural Network | 0.915 | 0.866 | 0.866 | 0.868 | 0.866 |
| | Logistic Regression | 0.946 | 0.893 | 0.893 | 0.893 | 0.893 |
| Cross Validation 5 | | | | | | |
| 3 | Model | AUC | CA | F1 | Precision | Recall |
| | KNN | 0.917 | 0.858 | 0.858 | 0.859 | 0.858 |
| | Neural Network | 0.917 | 0.850 | 0.851 | 0.858 | 0.850 |
| | Logistic Regression | 0.944 | 0.889 | 0.889 | 0.889 | 0.889 |

Table II illustrates the F1-score values by varying number of cross folds in training 5,10, & 20 respectively. From the graph it is observed that the F1-score values are highest for logistic regression for 10 fold cross validation with Neural network & KNN.

TABLE II F1 Score Comparison Chart

| F1 Score for Cross Validation 20 | | | | |
|----------------------------------|---------------------|-------|----------------|---------------------|
| 1 | | KNN | Neural Network | Logistic Regression |
| | KNN | | 0.333 | 0.117 |
| | Neural Network | 0.667 | | 0.113 |
| | Logistic Regression | 0.883 | 0.887 | |
| F1 Score for Cross Validation 10 | | | | |
| 2 | | KNN | Neural Network | Logistic Regression |
| | KNN | | 0.352 | 0.083 |
| | Neural Network | 0.648 | | 0.051 |
| | Logistic Regression | 0.917 | 0.949 | |
| F1 Score for Cross Validation 5 | | | | |
| 3 | | KNN | Neural Network | Logistic Regression |
| | KNN | | 0.568 | 0.114 |
| | Neural Network | 0.432 | | 0.113 |
| | Logistic Regression | | | 0.886 |
| | | | | 0.887 |

6 Confusion Matrix

For machine learning and AI domain for statistical classification analysis confusion matrix is used as error matrix. It displays performance of algorithms. In this point classification analysis is done for KNN classifier, Logistic regression classifier and neural network as classifier.

Figure 3 shows confusion matrix for KNN classifier. It shows 87% predicted value for tumorous images and 86% for non-cancerous images.

| | | Predicted | | Σ |
|----------|-----|------------|------------|------------|
| | | no | yes | |
| Actual | no | 86.7 % | 13.3 % | 98 |
| | yes | 12.9 % | 87.1 % | 155 |
| Σ | | 105 | 148 | 253 |

Figure. 3 Confusion Matrix KNN

Fig 4 shows confusion matrix for neural network classifier. It shows 87% predicted value for tumorous images and 89% for non cancerous images.

| | | Predicted | | Σ |
|----------|-----|------------|------------|------------|
| | | no | yes | |
| Actual | no | 89.8 % | 10.2 % | 98 |
| | yes | 12.9 % | 87.1 % | 155 |
| Σ | | 108 | 145 | 253 |

Figure. 4 Confusion matrix neural network

Figure.5 shows confusion matrix for neural network classifier. It shows 93% predicted value for tumorous images and 87% for non-cancerous images.

| | | Predicted | | Σ |
|----------|-----|-----------|------------|------------|
| | | no | yes | |
| Actual | no | 87.8 % | 12.2 % | 98 |
| | yes | 6.5 % | 93.5 % | 155 |
| Σ | | 96 | 157 | 253 |

Figure. 5 Confusion matrix Logistic Regression

7 Classification Results

As mentioned in confusion matrix there is Correct classification & missed classification s for tumor images and non tumor images. In this section result figures given according to classification model.

i) Logistic regression classification model: This model shows 93.5 % correct classification Figure.6 shows correct classification using Logistic regression. Figure. 6 shows Logistic regression correct classification images.

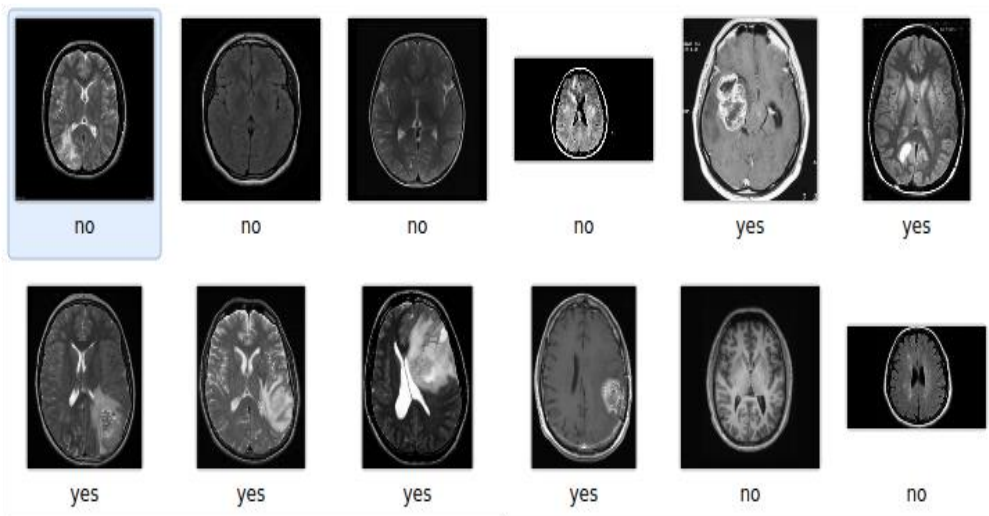


Figure. 6 Logistic regression correct classification

i) Logistic regression classification model: Model shows 87% miss classification. From the result we can analyze easily that even though there are tumors in images they are miss classified as no tumor in the image. Figure. 7 shows Logistic regression miss classification images.

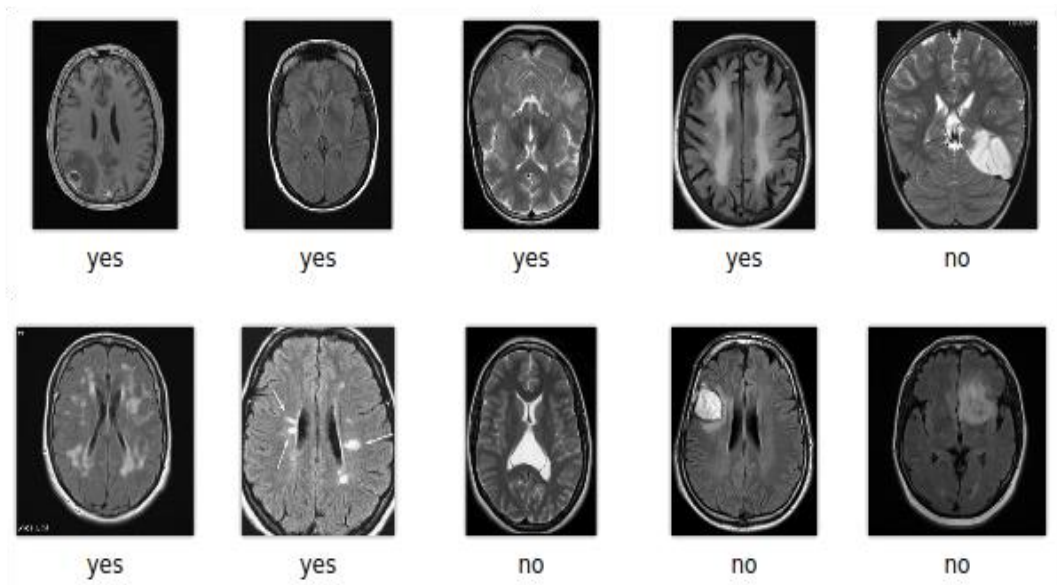


Figure. 7 Logistic regression miss classification

ii) Neural Network classification model: This model shows 87.1 % correct classification for tumor and non-tumorous images. Figure. 8 Neural Network correct classification images.

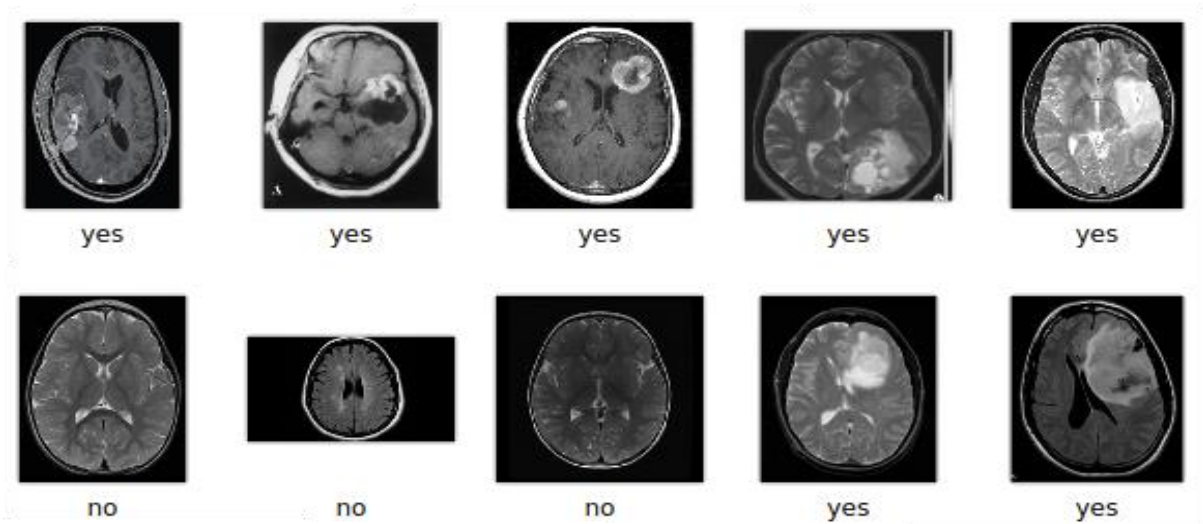


Figure. 8 Neural Network correct classification

ii) Neural Network classification model: This model shows 89.8% miss classification for tumor and non-tumorous images. Figure. 9 Neural Network miss classification images.

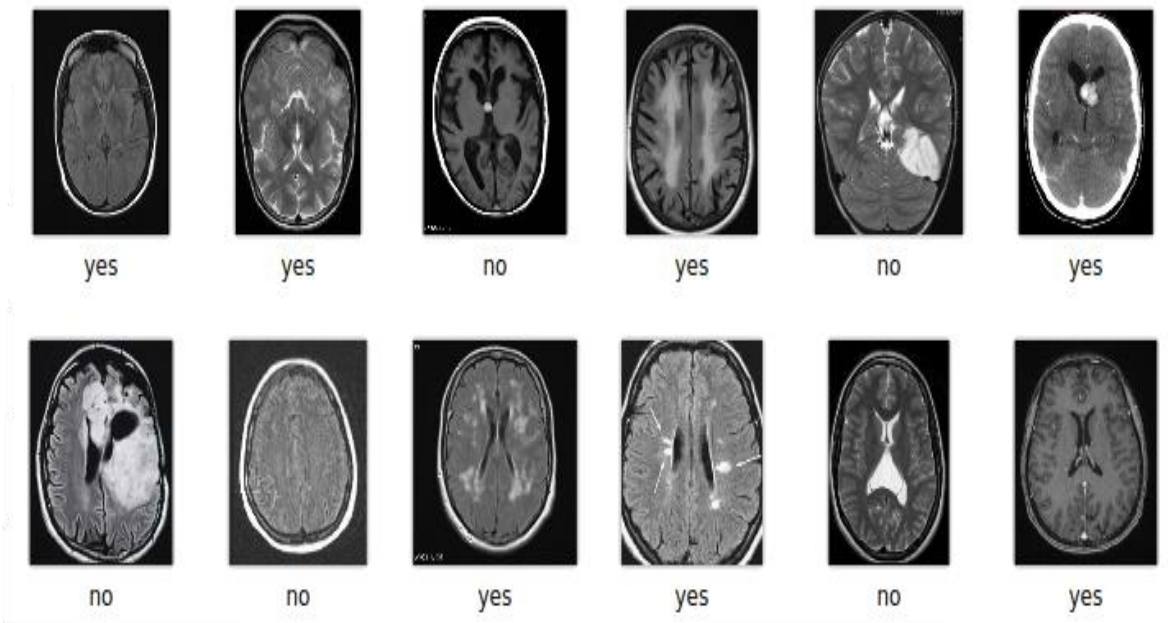


Figure. 9 Neural Network miss classification

iii) KNN classification model: This model shows 87.1 % correct classification for tumor and non tumorous images.

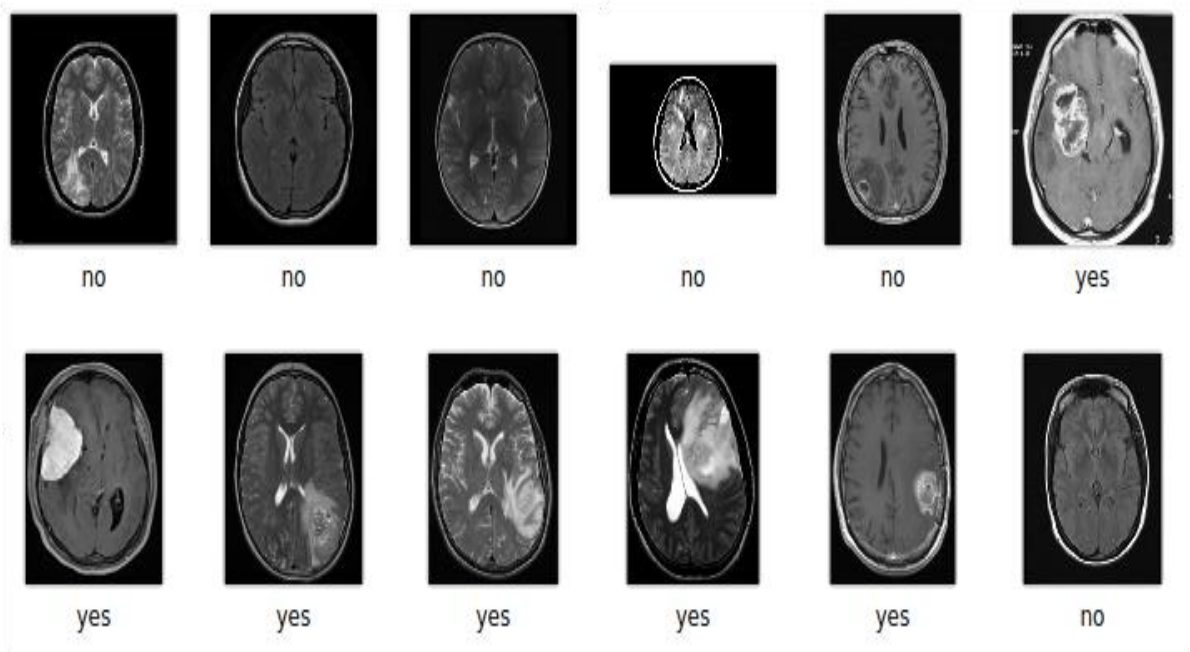


Figure. 10 KNN classification correct classification

iii) KNN classification model: This model shows 86.7 % miss classification for tumor and non tumorous images. Figure. 11 shows KNN classification miss classification images.

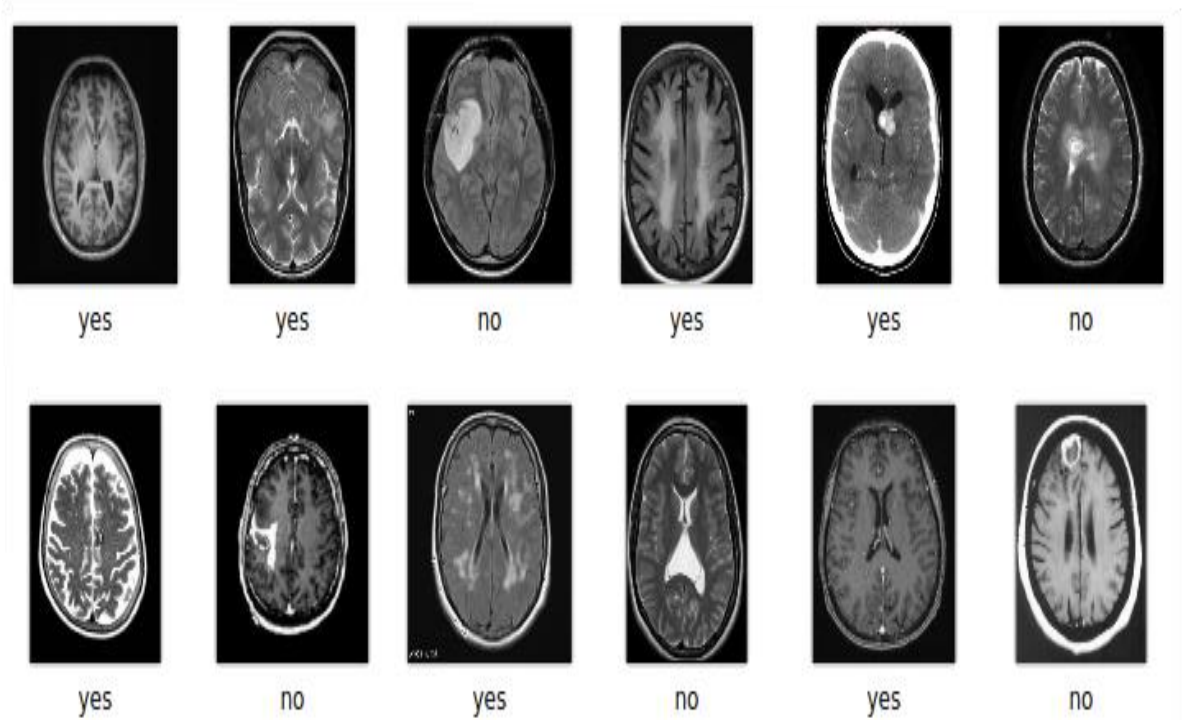


Figure. 11 KNN classification miss classification

8 Conclusion

In this work we proposed a different comparative classification analysis approach based on three different classifications based on deep learning feature extraction technique using VGG19 19 layer image recognition model trained on Imgenet. Since MRI data sequences different in terms of modalities but every modality contains rich information so feature exaction is very important task for classification. Our approach

demonstrated fair classification results without any human annotations. Based on selected classifiers all the classifiers gives accuracy above 90%with other state of art methods.

9 Future Scope

There are some suggestions for future work. Firstly, one can keep the primary objective is to detect, segment, and to identify various types of brain tumors with large dataset. Secondly the methods and techniques can be extended to colour images for the detection of the type of tumour without human annotation.

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