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CAPSULE NETWORKS: HOW EFFECTIVE IT IN BRAIN TUMOR DETECTION

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Abstract

Brain tumor is a critical disease and its accurate and timely detection is important for effective treatment. Several Deep Learning methods are present today to deal with and diagnose the disease on time. CNN is one of the most used Deep Learning techniques for image classification and it has significantly witnessed success in medical image processing, the main shortcoming of CNN is its inability to visualize and analyze spatial hierarchies. CapsNets are used to overcome this disadvantage. It gives more reliable classification results by including Dynamic Routing in place of MaxPooling layers, which is the main reason for the translation invariance in CNN. Dynamic Routing is the brain of CapsNet. The paper uses a public MRI dataset. The proposed model achieves an accuracy of 95.5% and outperforms DL techniques like VGG16, ResNet, and AlexNet. The main performance matrices that are used by this study are Accuracy, Precision, Recall, ROC-AUC. As the comparisons shows that the proposed technique is performing best out of the given techniques.

Keywords: Capsule Networks, MRI, Brain Tumor, Deep Learning, Accuracy.

1. Introduction

Artificial intelligence makes it easier to detect any fatal disease on time. Manually inspecting the patient's data is time-consuming and can impact a patient's life. It is quite effective to analyze the images of an organ using AI tools and techniques as it is quite accurate and less time-consuming. Several AI techniques are present today to predict the disease. Machine learning is one field of AI used primarily to predict the occurrence of a disease. The human body is very vulnerable today, and anyone of any age can get any disease. It becomes crucial to detect or predict the possibility of any disease at the right time so that a person's life can be saved. Machine learning techniques help medical practitioners to do the same. It takes the medical data the healthcare facilities generate and processes it for a certain conclusion or outcome.

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Figure 1 covers all the terms that are frequently used in this paper. The terms Deep Learning, Brain Tumor, MRI Images, Performance Matrices, Dynamic Routing, and Capsule Net will be discussed in the paper several times. Hence pictorial representation is provided for these terms.

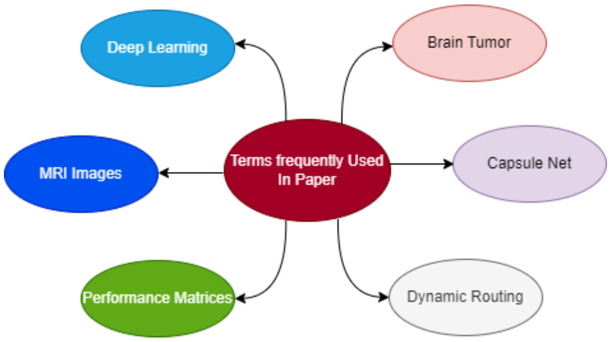

Figure 1. Terms Frequently Used in the Paper

Nowadays the data generated is huge and machine learning techniques cannot process it and make accurate predictions. [1]. Deep learning techniques help medical experts to overcome this limitation of machine learning techniques. The DL technique tries to imitate the working of human behavior by adding layers known as hidden layers to refine the prediction results. Collecting suitable data for disease prediction is also crucial. Several ways are there to collect the data. i.e. CT Scan, PET, MRI. MRI images are best suited to detect and treat the disease. The BT is one such disease that is quite serious and fatal and a group of medical practitioners is always working in the direction of its treatment. Several deep-learning models are adapted to predict brain tumors. A brain tumor is a medical condition in which the cells in the brain start to grow in an uncontrolled manner [**2**]. This abnormal growth leads to extracranial pressure and affects the normal day-to-day working of the body parts. These can be categorized into two types Benign and Malignant. A benign tumor is not lethal but it can drastically affect the working of the body parts. The malignant tumor is life-threatening. The cancer can be further subcategorized to Grade I, Grade II, grade III, and Grade IV. Out of these, Grade I and Grade II are of Benign Tumor and the rest of the two grades are of Malignant Tumor. Definition of Grades of Tumor. Grade I and Grade II tumors generally spread slowly in the human body [3]. They are not that dangerous and can be effectively treated if early detection exists. Grade III and Grade IV are aggressive and are considerably fatal [4]. Generally, an MRI of a patient's brain is mostly preferred by clinicians because it gives a clearer view of the inner structure of the human brain. It gives better segmentation between healthy and unhealthy tissue.

Figure 2 represents different techniques used to predict and detect brain tumor i.e. Machine Learning and Deep Learning these are further classified for the techniques for eg. In ML SVM, LR, RF, DT techniques are used, and in Deep Learning techniques like CNN, 3D-CNN, Transfer Learning, GAN, CapsNet are used.

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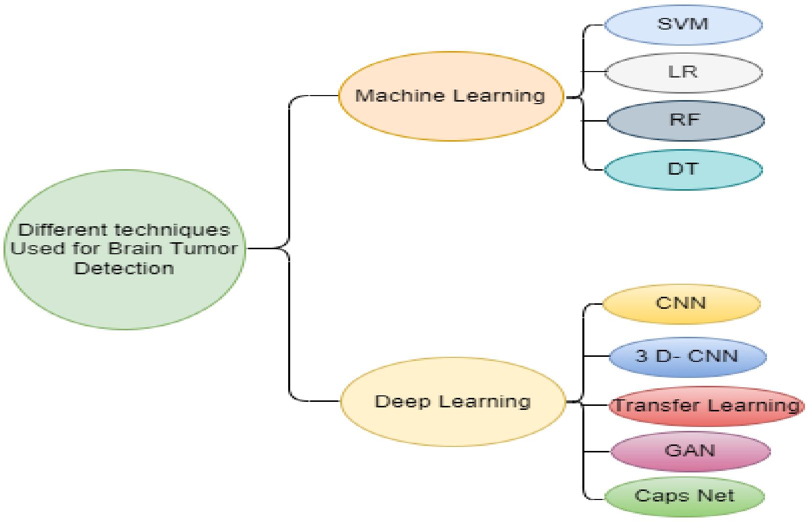

Figure 2. Different Techniques Used to Detect Brain Tumor

Several deep learning techniques are present and used by the researchers to predict and classify the tumor. These are AlexNet, ResNet, LeNet, GoogleNet, RNN, DBN to name a few. Out of these present methods, CNN is most used. CNN dominates other models used for image processing because of its exceptional performance in classifying the tumor[5]. CNN trains the model by adding additional layers known as hidden layers to extract the desired and most adequate features. CNN uses the Maxpooling layer to extract the desired features from the given images. It plays a crucial role in extracting the features. The MaxPooling layer has the disadvantage that it is transition invariant. If the position of a given image is flipped or changed it is not able to detect the change and classify the image efficiently. So, there is always a need for a better method which can overcome these drawbacks and perform better to classify brain tumor. Researchers are working in this direction to find a better technique that reduces the limitations of CNN. Sabour et al. introduced Capsule Network as a new technique that overcomes the drawback of the CNN maxpooling layer. Capsule Network is a collection of neurons known as capsules, to represent more complicated features. The maxpooling layer of the CNN is eliminated in the capsule networks. The brain of the Capsule network is the routing-by-agreement mechanism known as dynamic routing and it is used to find a path that connects the capsules of the input layer to the output layer [6]. That is the reason it can detect patterns accurately even after the images are flipped or rotated. Capsule layers are concatenated with convolutional layers to form a capsule neural network [7]. It extracts the features from the images of the brain and then classifies whether it is tumorous or not. The detection of brain tumor is error-prone due to is ever-changing form, shape, and size, The Capsule network helps medical experts to predict them accurately. The paper gives a capsule network-based approach to detecting the brain tumor.

The paper is arranged as follows: section 2 covers the review of work done by the researchers, section 3 discusses the material and methodology used, section 4 discusses the performance criteria used to evaluate the proposed technique, and Section 5 discusses the results and

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analysis. Section 6 will discuss the conclusion and future directions for the work and Section 7 covers the references used for work.

2. Literature Review

This section will discuss the work done by the researchers in various models for brain tumor detection and the motivation for the proposed techniques. It will cover the summarization of all the papers that have been studied to develop and propose a new technique that will help to predict brain tumor more accurately and with more refined results.

The authors of the paper [8] discussed the role of different Deep Learning models in medical image processing. The paper takes U-Net, DeepLab, and DenseNet models for its study and analyses that Densenet gave the best accuracy measures as compared to DeepLab and U-Net.

The author and his team in the paper [9] proposed a method of opposition-based Crow search (OCS) for the classification of diseases, in the paper different diseases like lung cancer, brain tumor, and Alzheimer. The implementation was performed on MATLAB and the proposed model has performed well while giving an accuracy of 95.22%, it gave a sensitivity of 86.45%, and a specificity of 100%.

[10] proposed a method on CNN in which the output layer produced a four-dimensional vector related to four categories of the BT. The model has successfully achieved an accuracy rate of 99%. It has been suggested that it is possible to extend the work to classify the tumor in more categories.

The paper [11] author has compared the performance of different DL model in the BT detection. It has used six DL models i.e. SVM, KNN, MLP, LR, NB, and RF for the tumor prediction were implemented through scikit-learn. After that, it also implemented the CNN for tumor detection using Tensorflow and Keras, and analyzed CNN performed well compared to other models with an accuracy of 97.87%.

In the paper [12]the author CNN-based automated brain tumor recognition method to classify the tumor. It compared the model's performance with the different CNN architectures i.e. AlexNet, VGG16, GoogleNet, and RNN. It has achieved an accuracy of 98.67% for CNN AlexNet after the tuning of hyperparameters of AlexNet.

[13] proposed a new hybrid deep convolution neural network and deep watershed auto-encoder (CNN-DWA) model to predict the BT. The performance of the proposed technique has been compared with the CNN, DNN, and DWA to analyze its effectiveness in tumor detection, it has used the 5 datasets i.e. BRATS2012, BRATS2013, BRATS2014, BRATS2015, and ISLES-SISS 2015 for the experiment purpose. It has been observed that the accuracy of the proposed model is approximately 98%. Which is best as compared to other models.

[14] proposed an enhanced CNN Model to detect brain tumor detection. The model has iterated for 20 epochs and achieved an accuracy of 99.59 %. The proposed approach has been compared with the pre-existing techniques to show its effectiveness in the field of tumor detection.

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Different machine-learning techniques used to detect breast, brain, lung, liver, skin cancer, and leukemia are compared in [15]. Different papers on different cancer malignancies were reviewed and the role of machine learning was analysed. The paper gives an insight into different machine-learning methods which are used for cancer detection. The main datasets that have been used for the study of different tumors are BRATS 2015, 2016, and 2018 for brain tumor, LIDC-IDRI for lung cancer, WBCD for breast cancer, and many others.

BoostCaps was used to classify the brain tumor in [16]. A boosted capsule network was proposed that takes the advantage of boosting method to handle weak learners. It was the first capsule network model that incorporated an internal boosting mechanism. Overall accuracy of 92.45 % was achieved. Since the dataset that was chosen was very small the suggestion for a larger dataset was given[17.]

A new approach known as the Bayesian approach to classify brain tumor using a capsule network was adopted by [18]. Since the capsule network does not capture the prediction uncertainty, BayesCaps was implemented to overcome the drawback. An initial accuracy of 68.3% was achieved but finally, the model was able to achieve 73.9% accuracy. It is concluded that sorting the uncertain prediction at multiple limits can gradually improve the accuracy.

Parnian Afshar et.al.[19] the paper studied the role of the capsule network in classifying the brain tumor on the basis of MRI images and course tumor boundaries. It gave an accuracy of 90.89% i.e. classification accuracy by the proposed approach was increased. The proposed architecture eliminated the need for tumor exact annotation and the proposed Capsnet focused on the main area.

3. Methods and Methodology

The section will discuss the dataset used for the classification task. The parameters are considered to make the dataset convenient for the classification before feeding it into the training and testing its performance.

This section will cover:

a) Experimental Setup

b) DataSet Used

c) Preprocessing of the dataset

d) Feature extraction

e) classification

Figure 3 shows the basic process of classification in which the first step is dataset collection then it is preprocessed after preprocessing feature extraction is performed and training and testing ratio are used for dataset division and is fed to the trained model for classification.

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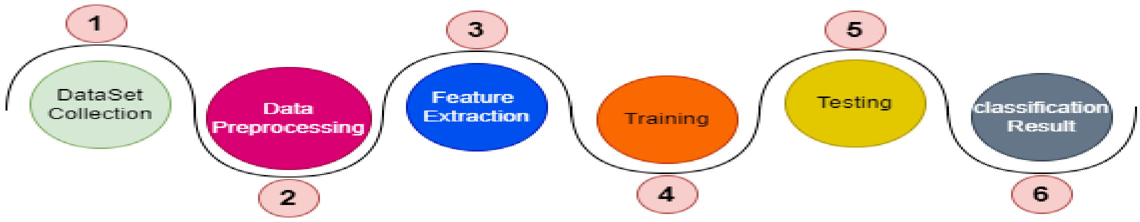

Figure 3. Basic Flow of Classification

3.1 Experimental Setup

The classification is performed on AMD Ryzen 5 7520U with Radeon Graphics and Windows 11. It is performed in Python version 3.11. The experiment is carried out in a GPU environment. Our experiments have used multiple Python libraries, such as Tensorflow, Matplotlib, Numpy, etc., to name a few. We have used the cloud environment of Google Colaboratory, i.e. Google Colab, for our work.

3.2 DataSet Used

The paper used the MRI image dataset of the brain tumor publicly available at the Kaggle. The dataset has a total of 3060 images which are divided into three directories with the name: Yes, No, Pred. the photos are properly labeled with yes, or no labels. There is a training, and testing, and validation ratio of 80:20 for the classification.

a) Yes: This folder consists of the images of the brain have a tumor.

b) No: This folder consists of the images of the brain that do not have a tumor.

c)Pred: This folder consists of images of the brain used for testing or predicting the tumor.

Table 1 summarizes the dataset used in the proposed model. It shows the number of images present in different folders.

Table 1. Dataset Description

Folder Name	No of Images
Yes	1500
No	1500
Pred	60

3.3 Data Preprocessing

it is necessary to clean the dataset to make it appropriate and suitable for the classification task. The original dataset or the images have impurities that it is not considered good for training purposes. These images can be duplicated, or distorted, and sometimes the noise is also present,

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so it becomes important to preprocess the original dataset so that the presence or absence of the tumor can be predicted accurately and further treatment can be done accordingly. Many preprocessing techniques are present today that help to clean the data i.e. grayscale, resize, handling the missing data, redundancy reduction, etc.

Figure 4 shows how the preprocessing is performed to produce the refined data from raw data, because it is not suitable for classification.

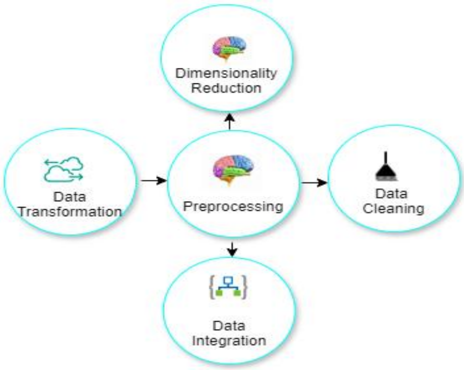

Figure 4. Preprocessing Steps

3.4 Feature Extraction

Feature extraction is also important in tumor classification. It is essential to take out the good features and then analyze these features to improve the classification accuracy. Feature extraction means extracting some important information from the raw data and utilizing it for efficient task accomplishment. Several feature extraction methods are present to extract the features. Like VGG16, VGG19, etc. CNN is most commonly used to extract the features. The proposed technique also used CNN for feature extraction. After extracting the important feature capsule network is used to classify the images.

3.5 Proposed Methodology

In this paper, we have proposed a technique, in which the drawback of the CNN is eliminated using the Capsule network. The existing CapsNet architecture is updated by adding more routing layers to refine the classification results, as well as some customization is also performed on the activation function. In this study, tumor prediction will be done by analyzing the image dataset after the necessary preprocessing. In this section, the architecture of the Capsule Network will be discussed in detail. After that there will be a discussion about the changes that are performed in the architecture:

Capsule Network: A Capsule Network is a group of capsules that create a network. Capsules are the group of neurons collected together. The output of the capsule network is vector instead of scaler output as in the case of CNN. The vector output of Capsule Network gives us additional information about the pose, and how strongly a feature is present or not. The main focus of the capsule Network is to learn the relationship between different parts of the image. The foundation of capsule network is Dynamic routing or Routing -Agreement. Dynamic

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routing occurs between these lower and higher-level layers i.e., Primary Caps and Digit Caps. It keeps track of the record that higher-level capsules receive input from the most appropriate or compatible lower-level capsules, assisting the network in learning the relationship between the spatial differences i.e., the difference between the pose and its orientation.

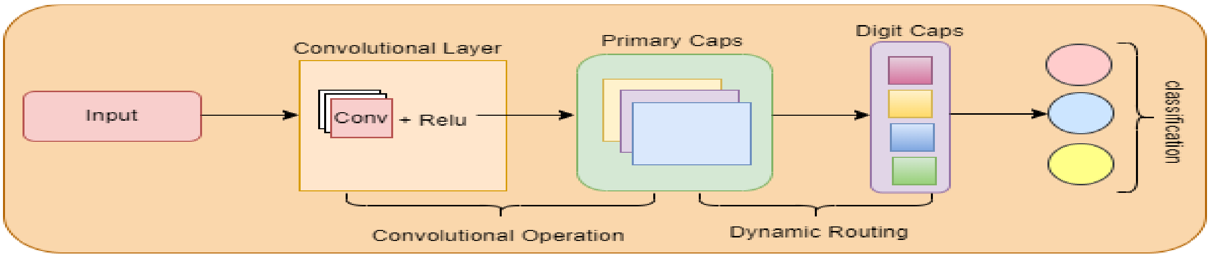

Fig 5. Architecture of Proposed Network

In figure 5, it can be seen that the initial layer is a convolutional layer which helps in the feature extraction. Multiple convolutional layers can be included to pull out the most efficient and relevant features. After the extraction, features are forwarded to the primary capsule layer and the grouping of the feature/neuron is done as a capsule. This layer is responsible for preserving the spatial information and after the advanced feature extraction the capsules are fed to the next higher-level layers for deeper feature analysis and the classification of the tumor. Here the dynamic routing gives its contribution between primary caps and digit caps. It is responsible for forwarding the most appropriate neurons based on the vector output and it is called the brain of the capsule networks. As it is clear from the figure the max-pooling layer of the CNN is eliminated which was the major drawback of the CNN. The shape of the images that are fed for the classification is converted to 128X128. It has used two convolutional layers and one primary caps layer.

4. Performance Analysis

It is desirable and crucial to compute the efficiency of the proposed technique and analyze its efficiency in classifying the images and whether it can assist medical practitioners in the right way. Several performance evaluation criteria are present to measure efficiency. In this section, we will discuss the currently present performance matrices

1) Accuracy: Accuracy measures how accurately the model can classify images. It measures the model performance based on its capability to classify the images.

Accuracy=(TN+TP)/(TP+TN+FP+FN)

2)Precision: Performance is also measured using the Precision. It is measured when true positive is divided by the total positive predictions made by the model.

Precision=TP/ (TP+FP) (1)

3)Specificity: the ratio of actual positive instances out of all the present instances.

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Specificity=TP/ (TP+FN)
(2)

4)Sensitivity: The ratio of the true negative instances present.

Sensitivity=TN/ (TN+FP)
(3)

4.1 Result Discussions

The section will cover the classification outcomes of the proposed technique and then analyze its performance. Then there is a discussion about the efficiency of the model. The model is run for 150 epochs having 6 routing layers. Table 2. below lists the classification report of the model.

Table 2. Performance of the Model for Different Matrices

Model	Accuracy	Precision	F1-Score	Recall	ROC-AUC
Proposed (CapsNet)	0.9550	0.95	0.96	0.95	0.98

Figure 6. discusses the accuracy and loss of the proposed model. As can be seen from the figure it represents both the training loss and validation loss as well as the training accuracy and validation accuracy. The proposed model successfully classifies the images with 0.9550 accuracy. and the loss of the model is 0.115. The model is performing well as analyzed according to the parameters.

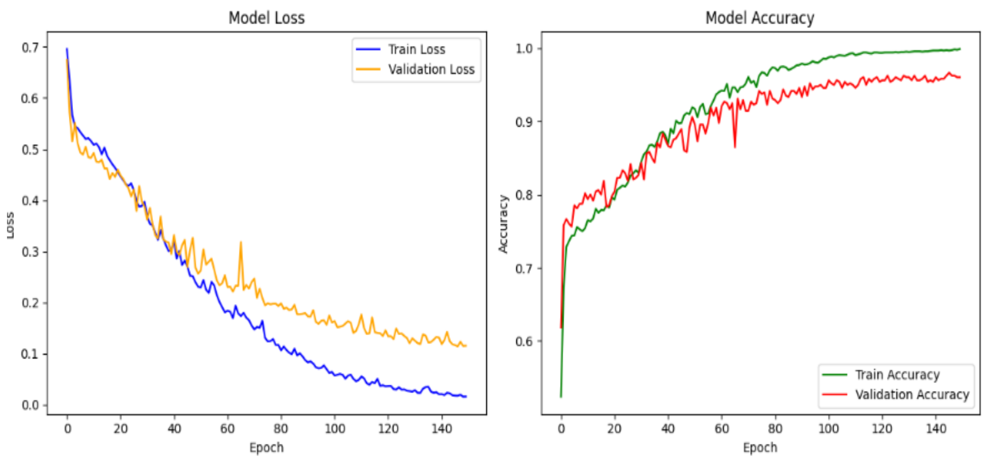

Fig 6. Loss and Accuracy of the Proposed Model

Figure 7 represents the ROC curve for the proposed work. The ROC-AUC is generally used to evaluate the performance of the model i.e. how efficiently it is performing the classification task. The higher the value of the ROC-AUC the better the model is differentiating between the

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classes. For the proposed model The AUC for Yes is 0.98, and for No it is 0.97, stating that the model is quite efficient and it is predicting the results well.

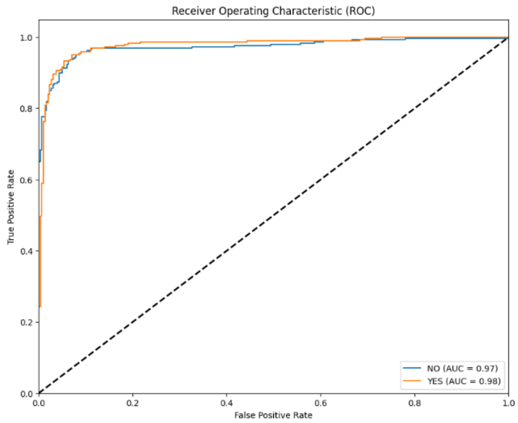

Fig7. ROC of the Proposed Model

Figure 8 represents the CM of the proposed model. A confusion matrix is used to test the performance model, and how accurately the model is classifying the images. By using a CM, other performance matrices i.e. accuracy, precision, recall, and f-1 score can be calculated. The confusion matrix of the model represents that the model is accurately differentiating between the classes so the model is performing well.

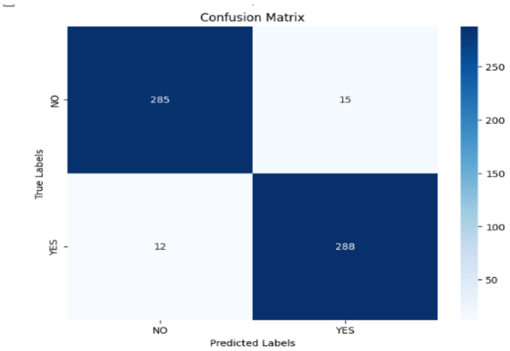

Fig 8. Confusion Matrix of the Proposed Model

Figure 9 shows the performance of the proposed model at epoch 25, 50,75,100 and 150 as well.

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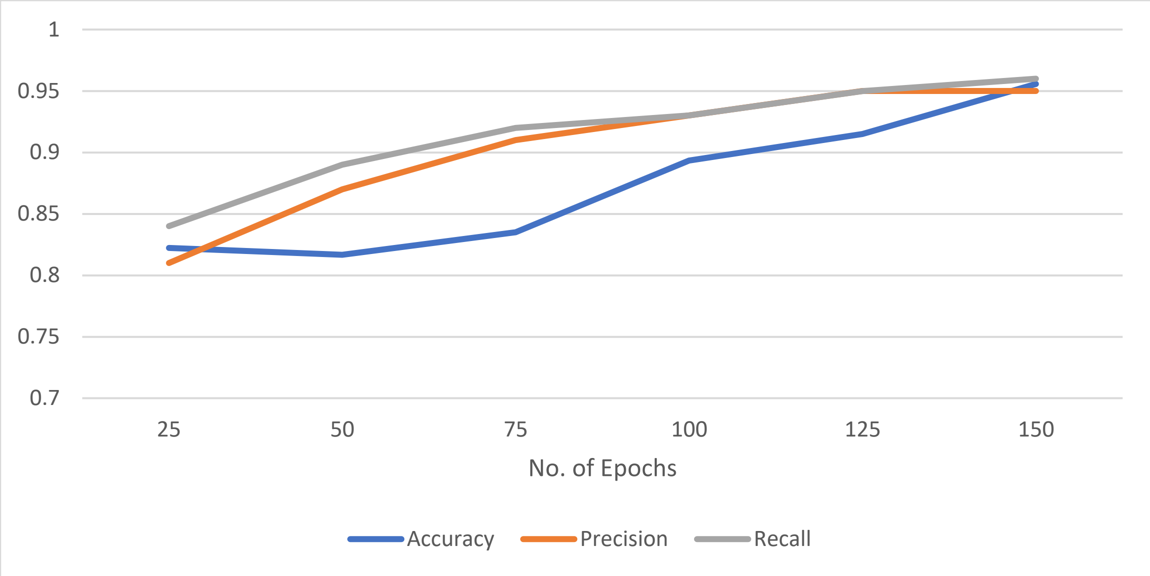

Fig 9. Performance of the Proposed Model at Different Epochs

Figure 10 shows the performance of the proposed model in a graphical representation. It shows the different performance criteria achieved by the model.

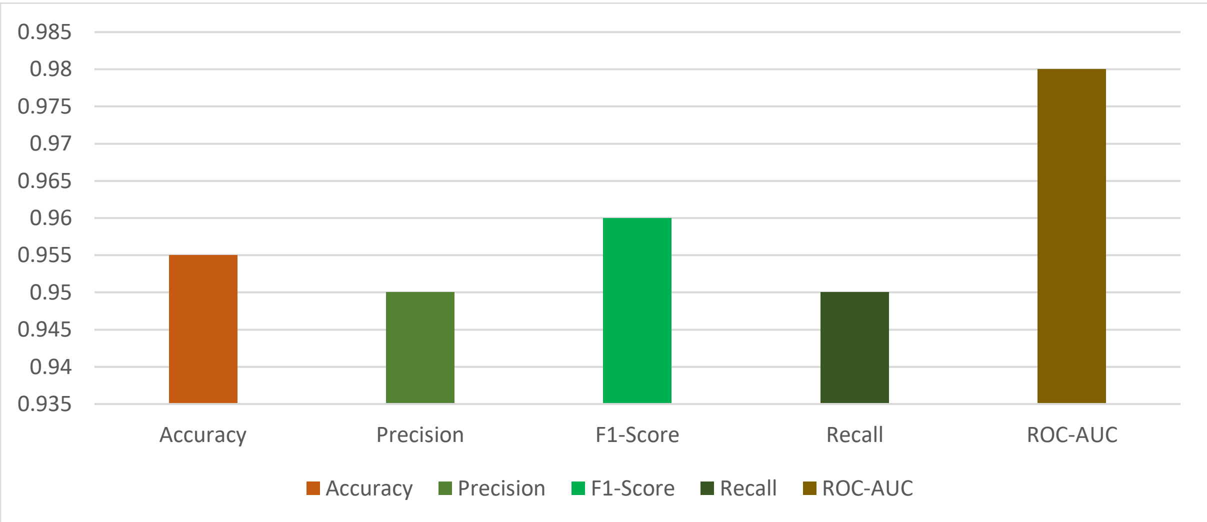

Fig 10. Performance of the Proposed Model

4.2 Comparison with the Pre-Existing Techniques

Now we will compare the performance of the proposed technique with other pre-existing deep learning models. Many performance matrices are used for the comparison. In Table 3, the performance is compared with VGG19, VGG16, ResNet 101, AlexNet. It can be analyzed that the proposed model is performing best in terms of accuracy as well as precision and recall.

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Table 3. Comparison of the Proposed Technique with Pre-Existing Techniques

Model	Accuracy	Precision	Recall	ROC-AUC
VGG19	0.9183	0.9298	0.9153	0.9954
VGG16	0.9440	0.9335	0.9430	0.9745
ResNet 101	0.8667	0.8556	0.8662	0.9554
AlexNet	0.9502	0.9500	0.9502	0.9941
Proposed Model (CNN+CapsNet)	0.9550	0.9550	0.9602	0.9880

Figure 11 gives a comparative view of the Accuracies of different techniques with the proposed techniques. It shows that the capsule network gives the highest accuracy among all the present state of the art techniques.

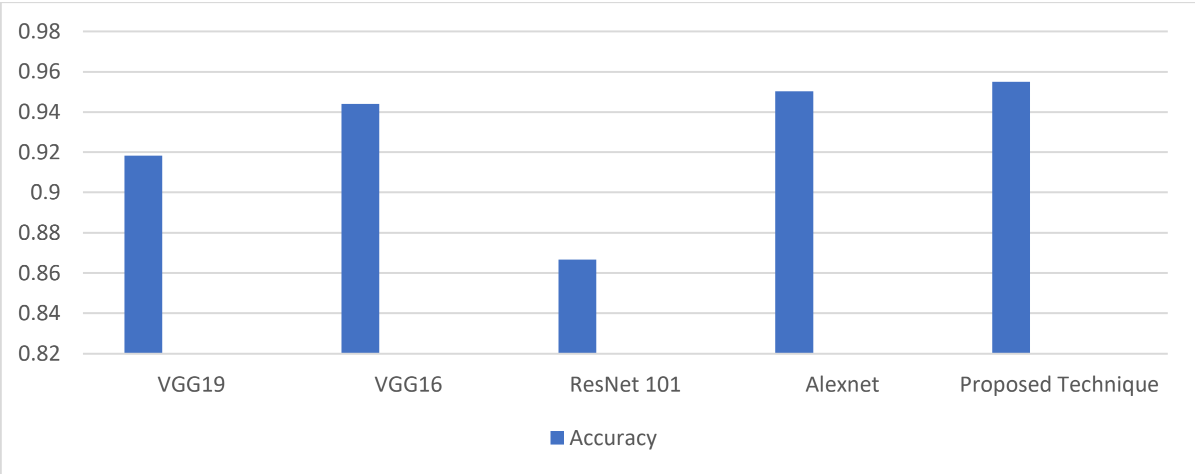

Fig 11. Comparison of the Different Models based on Accuracy

Figure 12 shows the performance of the different models based on the different performance criteria.

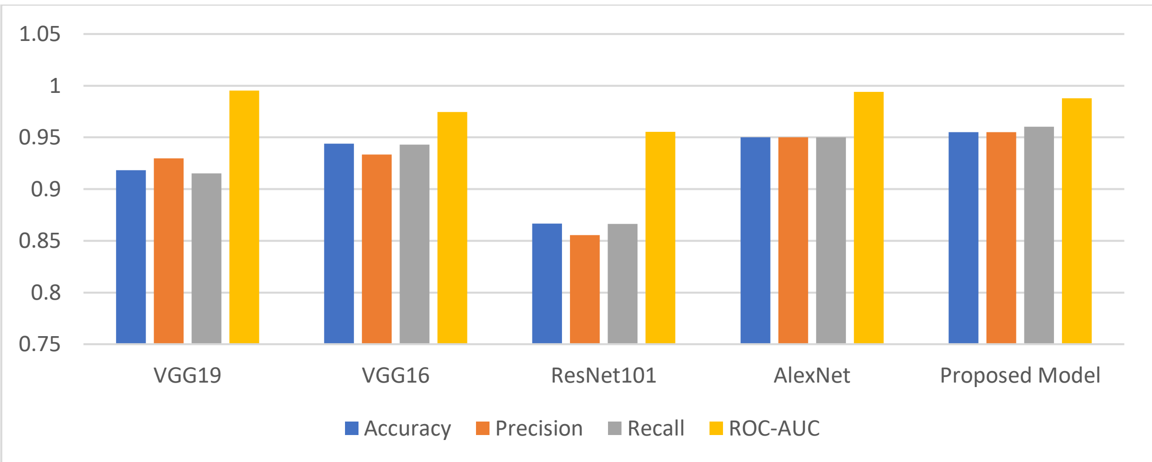

Fig 12. Performance Comparison of Different Models Based on Different Matrices

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Figure 13 Compares the ROC-AUC of the different techniques.

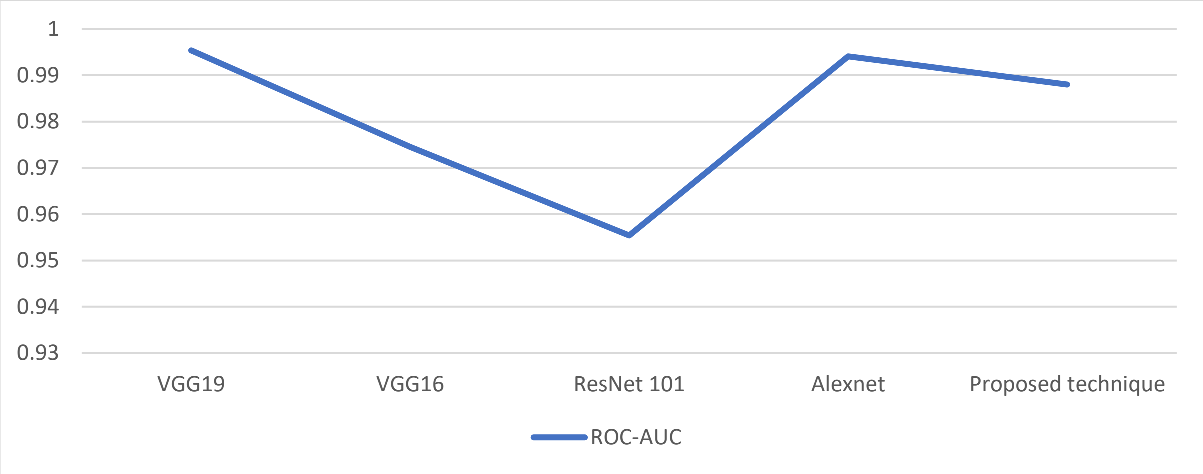

Fig 13. Performance Comparison of Different Models Based on ROC-AUC

5. Conclusion

As brain tumor is an increasing threat to human beings it is necessary to detect it on time. In the paper impact of capsule networks has been studied and the impact of the proposed model has been analyzed. it is observed that the capsule network outperformed the pre-existing techniques that are used to tell the onset of brain tumor. However, the dataset that is used by the experiment is of smaller size so it is questionable whether the proposed model also performs well with the real-life data or not. In the future, there will be an effort to collect real-world data and implement the proposed technique on it. Further, new feature extraction techniques can be combined with the capsule network to make it more effective to find the most suitable feature extractor and to detect the brain tumor on time.

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