2024 IEEE 13th International Conference on Communication Systems and Network Technologies (CSNT) | 979-8-3503-0546-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/CSNT60213.2024.10546139

Brain Tumor Diagnosis Using Hybrid Pre-trained CNN-SVM

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***Abstract*—One of the most crucial and challenging jobs in the world of medical imaging is the detection of brain tumors. Manual classification with human assistance can lead to inaccurate predictions and diagnoses. Further, this is a very difficult task when a substantial volume of data must be supported. Brain tumors are highly variable in appearance and similarities between tumors and normal tissue make extraction of tumor regions from the critical image. Early detection of tumors and classifying them, whether cancerous or non-cancerous are very helpful to the patient. We have proposed a hybrid model using pre-trained CNN (Convolutional Neural Network) named as the EfficientNet B3 model and Support Vector Machine(SVM) classifier in this work boosting detection and finally classification of tumor images. There are eight categories of the EfficientNet model i.e. B0-B7. From eight categories, we have used the EfficientNet B3. Because this model gave more accuracy and requires less computation time. In our model, EfficientNet used as feature extractor and SVM used as the classifier. The accuracy of our proposed hybrid model is 99%. The primary objective of this study is to identify categorize tumors into three types: glioma, malignant, and pituitary after correctly identifying them from non-tumor images.**

***Index Terms*—Convolutional Neural Network (CNN), EfficientNet B3, Support Vector Machine(SVM), Magnetic Resonance Image (MRI), Feature Extraction, Classification.**

I. INTRODUCTION

Cancer is an uncontrolled expansion of anomalous cellsin the body. Cancer develops when the natural regulatory systems fail in the body. Instead of decomposing, old cells expand uncontrollably and introduce new, odd ones. Tumors are growths of tissue composed of extra cells. Brain tumors are abnormal aggregates of cells that proliferate and multiply out of control in the brain. Doctors do several tests to identify the disease and a brain tumor's kind. Brain scansare used to analyze tumors. In the medical field, the use of AI has recently become a hot topic. Artificial intelligence magnetic resonance image (MRI) classification is of great interest in medical image analysis. There are two common ways to classify brain tumors. The first is to classify brain images into normal or abnormal classes, and the second isto classify different stages of brain tumors.

MRI or CT scans are commonly used to survey the analysis of the brain. The entire process is certified in this paper using MRI scans. MRI scan is more useful than CT scan for diagnosis. There is no bad effect on the human body. It works using magnetic fields and radio waves. Numerous algorithms have been developed for the diagnosis of brain tumors. But may have some drawbacks in terms of identification and extraction. Compared to computed tomography (CT) and some other techniques, MRI imaging can create high-contrast images of the brain and is safer. Similar tothis, the high resolution of the pictures produced by MRI scans allows for the extraction of a wealth of data regarding brain organization and analysis at once available. It has a tremendous benefit for image analysis.

Four standard sequences are available which are usedin the MRI scan modal: T1-weighted MRI, T2–weighted MRI, T1-weighted, FLAIR and T1-weighted with contrast. In general, T1-weighted contrast enhancement is the most commonly used as it simple explanation of healthy tissue. The MRI shows brain tumor as the brightest area. The quantity of hydrogen atoms in the body was used by MRI to construct images. If there are a lot of hydrogen atoms in a particular area, the region will appear brighter. Tumors also appear as bright regions because they have the highest number of hydrogen atoms at. If the tumor is not clearly visible on a regular MRI, an agent can be used to help highlight the contrast. An MRI contrast agent is gadolinium. There is a lot of glucose in gadolinium, and there is a lot of hydrogen in 3 glucose. It is known that tumors ingest glucose, making themhydrogen-rich and appearing brighter on MRI scans. Brain MRIs are taken and features are extracted for automatic tumor classification. After feature extraction, a classificationmodel can be employed on these extracted features and toclassify the tumor type. A convolutional neural networkis a combination of a feature extractor and a classifier.Convolutional layers extract features, while fully connected layers conduct classification based on the extracted features.In this paper, we have used the hybrid model using a pre- trained hybrid Convolutional Neural Network (CNN) andSupport Vector Machine (SVM). This model provide theaccurate diagnosis and classification of brain tumors. The features are automatically extracted

979-8-3503-0546-3/24/$31.00 ©2024 IEEE
DOI: 10.1109/CSNT.2024.141

through the EfficientNetB3 [1] and SVM used as classifier, It will classify the braintumor by using these extracted features. Early detection oftumors and classify them, whether these are cancerous or non-cancerous are very helpful to the patient.

The main contribution of this paper are following-:

- We've successfully integrated a CNN (Efficient B3) model with Support Vector Machine.
- Integration of SVM model instead of a single fully connected layer better classifying tumor images.
  - We've used square-hinge loss for classification at the svsts.

The different types of brain tumor images are shown in fig.1.

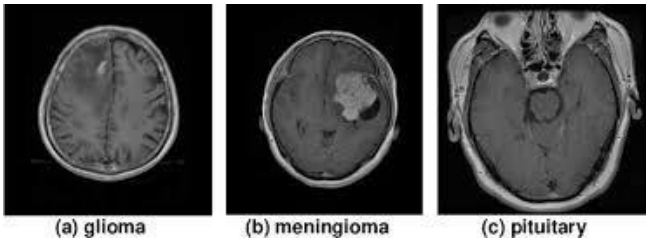

Fig. 1. Brain Tumor MRI Images a.) Glioma b.) Meningioma c.) Pituitary

II. Literature Review

Machine learning approaches are widely used in different domain such as medical diagnostics and preventive medicine. Specifically, using magnetic resonance imaging, a limited number of studies have concentrated on the diagnosis of brain malignancies (MRI). In most cases, ML techniques use MRI data to test and train conventional machine learning (ML) systems. Recently, several approaches have used deep learning (DL) for diagnosis of brain tumors.

Dmytro Filatov et al. [2] discussed many different models and it was appeared that EfficientNet B1 model are more implicit than the other models with width, depth, and resolution scaling properties. They obtained the accuracy of their model up to 90%.

Driss Lamrani, et al. [3] proposed detection and classification method of the highest levels of accuracy were shown in other neural network models using MRI pictures. These images were preprocessed and convolutional neural networks process data after it has been resized. Trainingand validation were implemented on 3,000 high-resolution MRI images. CNN model performance is evaluated usinga number of evaluation metrics. By means of this test, they found that the proposed model outperforms other CNN models in numerous performance areas. And they obtained the accuracy of model up to 98%.

Rehman, et al. [4] proposed a model in which they classified by using three different convolutional neural network designs, we identify meningiomas, gliomas, and pituitary tumors among other forms of brain cancers (AlexNet, GoogLeNet, and VGGNet).In terms of classification and detection, the fine-tuned VGG16 architecture achieved best accuracy up to 98.69%.

Sakshi Ahuja, et al. [5] proposed a work in which they used the DarkNet model. This pre-trained DarkNet model has finished classifying brain tumors into multiple categories. It used the Momentum based Stochastic Gradient Descent optimizer for classification of tumor images, using a pre-trained DarkNet-53 model. They are proposed the methodology has the maximum accuracy of 99.60% and testing accuracy of 98.54%.

Another study proposed by Hassan Ali, et al. [6] used three distinct models for brain tumor identification and classification, including VGG 16 (456 sec. per epoch), ResNet (606 sec.), and Inception V3 (375 sec.). They compared to these three pre-trained CNN models and obtained the Inception V3 model provided more accuracy and took less computation time.

Ebrahim Mohammed Senan, et al. [7] proposed a work in which they used the hybrid model using Alexnet and SVM.Alexnet is a pre-trained CNN model which is used for feature extraction and SVM used as a classifier for the classification of the brain tumor. The model has maximum accuracy of 95.10%.

Using a CNN (Convolutional Neural Network) architecture created for multiscale processing, Francisco Javier D ıaz-Pernas, et.al [8] presents a fully automatic brain tumour segmentation and classification method in this research. They tested its performance using a dataset of T1-weighted, contrast-enhanced MRI images that was made available to the public. To augment the training dataset in order to prevent overfitting, elastic data transformation was used.The performance metrics attained fall within the top ten techniques from the BRATS 2013 benchmark. We contrastedour findings with those of seven additional brain tumour classification methods that made use of the same dataset. With a score of 97.3%, their technique produced the highest tumour categorization accuracy.

J. Seetha,et al. [9] research project is to develop an effective automatic brain tumour classification system with high performance, accuracy, and minimal complexity. Fuzzy C Means (FCM) based segmentation, feature extraction for texture and shape, and SVM and DNN based classification are used in conventional brain tumour classification.

Low complexity is present. However, computations take a long time and are not very accurate. The accuracy of the training is 97.5%. Similarly, validation accuracy is high and loss during validation is extremely low.

Sunanda Das, et al. [10] proposed the model in which the images are filtered using a Gaussian filter as part of the preprocessing, and the filtered images are then subjected to histogram equalization. The machine then uses the CNN model to classify the photos. The model was quite bulky with

an excessive number of parameters and was trained using a very tiny sample size of data. Thus, there is a chance of overfitting. Dropout regularisation, a regularisation technique, is applied to the model to prevent overfitting. During the training phase, it is beneficial for the model to concentrate on the most noticeable patterns. As a result, there is a higher likelihood of generalisation, maintaining the model's stability. The model's final results show that it is 94.39% accurate and has an average precision of 93.33%.

III. METHODOLOGY

In this paper, we have used the pre trained CNN model which work based on the transfer learning techniques for classifying the brain tumors. The EfficientNet B3 model is used for the automatic feature extraction and supportvector machine (SVM) classifier for the classification of brain tumors.

There are two phase for the brain tumor detection and classification -:

- Input the MRI dataset
- Image Pre-processing
- Feature Extraction
- Classification.

A. INPUT THE MRI DATASET

In this work, we have taken Magnetic Resonance Imaging(MRI) images of the brain as an input. The dataset is splitinto the training and testing set. The ratio of the splitting dataset is 80:20 respectively.

B. IMAGE PRE-PROCESSING

The pre-processing makes the input MRI dataset work with the EfficientNet B3 model. The 2-D (two dimensional) MRI images of the brain are of non-uniform size. The EfficientNet B3 model architecture requires the input dimensions of 300x300. Then, the 2-D images of the brain tumor have been reshaped in a uniform dimension of 300x300x3. And the input images which are taken that is in the formof RGB format (Red, Green and Blue format). So, we must convert the image from RGB to grayscale format for the better feature extraction.

C. FEATURE EXTRACTION

The features are automatically extracted by the Efficient- Net B3 model from the input MRI brain scan pictures. The depth, width, and resolution parameters are adjusted progres-sively in this pre-trained CNN design by using the effective compound coefficient. This kind of scaling increases the accuracy of our model.

D. CLASSIFICATION

For classification, the EfficientNet B3 model's layers are updated in accordance with the settings of the hyperparameters. This model includes the CNN layer that is Rectified Linear Unit (ReLU), global average pooling. This model isa pre-trained model so we have used the transfer learning techniques on this model [11]. We froze the final few layers in order to solve our issue. The output layer for classifying the tumor uses the SVM classifier.

E. EVALAUATION METRICS

CONFUSION MATRIX A confusion matrix isa metric used to evaluate the performance ofa model. Each element in the matrix indicatesthe number of correct or incorrect classifications made by the model for each class There are following parameter in the confusion matrix.

Accuracy-:It is the number of all correct predictions divided by the total number of the dataset.

$$Accuracy = \frac{TP\ + TN}{TP + FP\ +\ TN\ + FN}$$

Precision-:It is a metric that tells us about the quality of positive predictions.

$$P = \frac{TP}{TP + FP}$$

Recall-:It tells us about how well the model identifies true positives.

$$R = \frac{TP}{TP + FN}$$

F1-score-:It is the harmonic mean of precision and recall.

$$F1 = \frac{2 \times P \times R}{P + R}$$

The proposed hybrid model is trained on a vast amountof data, and training progress graphs are made using the outcomes of simulations. The suggested model does not have the deep learning overfitting and underfitting problems.

The recording of the classification report, including the accuracy, recall, precision, and F1 score, is found in Table

I. The model's stability is also displayed in this table.

F. ARCHITECTURE OF PROPOSED MODEL

We have used the hybrid model which is a combination of the convolutional neural network(CNN) an support vector machine(SVM) classifier. There are following layer in this architecture-: **Stem Convolutional Layers:** EfficientNet B3 begins with a stem of convolutional layers that reduce the input image size to 224x224x32.

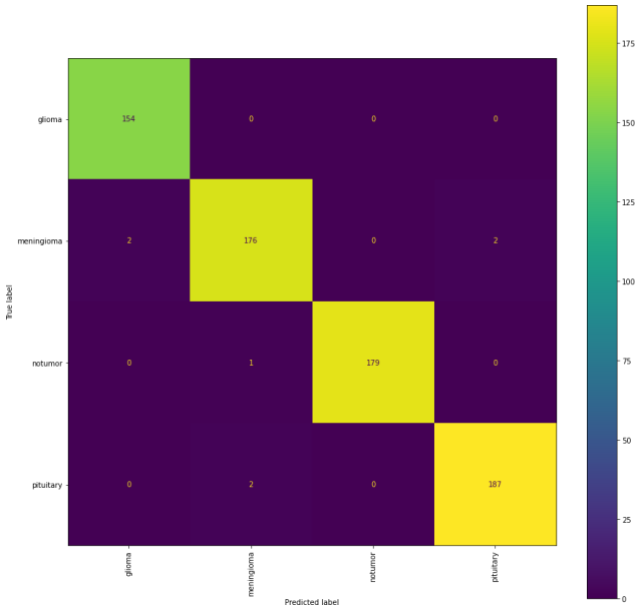

Fig. 2. **Confusion Matrix-:**It is multiclass confusion matrix which measurethe performance of all type of tumor.It shows the deviation and categorizedthe classes of brain tumor accurate and non accurate.

TABLE I

THIS HYBRID CLASSIFY THE BRAIN TUMOR IN FOUR DIFFERENT CLASSES.THESE ARE GLIOMA, MENINGIOMA, PITUITARY AND NO TUMOR. THE CLASSIFICATION DETAILS OF ALL THESE CLASSES ARE SHOWN IN THE TABLE.

	Precision	Recall	f1-score	Support
glioma	0.98	0.99	0.99	154
meningioma	0.98	0.96	0.97	180
no tumor	1.00	0.99	1.00	180
pituitary	0.97	0.98	0.98	189

Base Convolutional Blocks: The next stage consists of a series of convolutional blocks, each containing a combination of 1x1, 3x3, and 5x5 convolutions. These blocks use a technique called ”swish” activation, which is similar to the popular ReLU activation function but has been shown to improve performance.

Middle Convolutional Blocks: The middle stage contains a similar series of convolutional blocks, but with increased depth and width. These blocks use a different scaling factor than the base blocks to maintain a balance between accuracy and efficiency.

Top Convolutional Blocks: The final stage includes a series of convolutional blocks with an increased number of filters and a reduction in spatial dimensions. This stage is followed by a global average pooling layer, which averages the feature maps across spatial dimensions to produce a fixed-length feature vector.

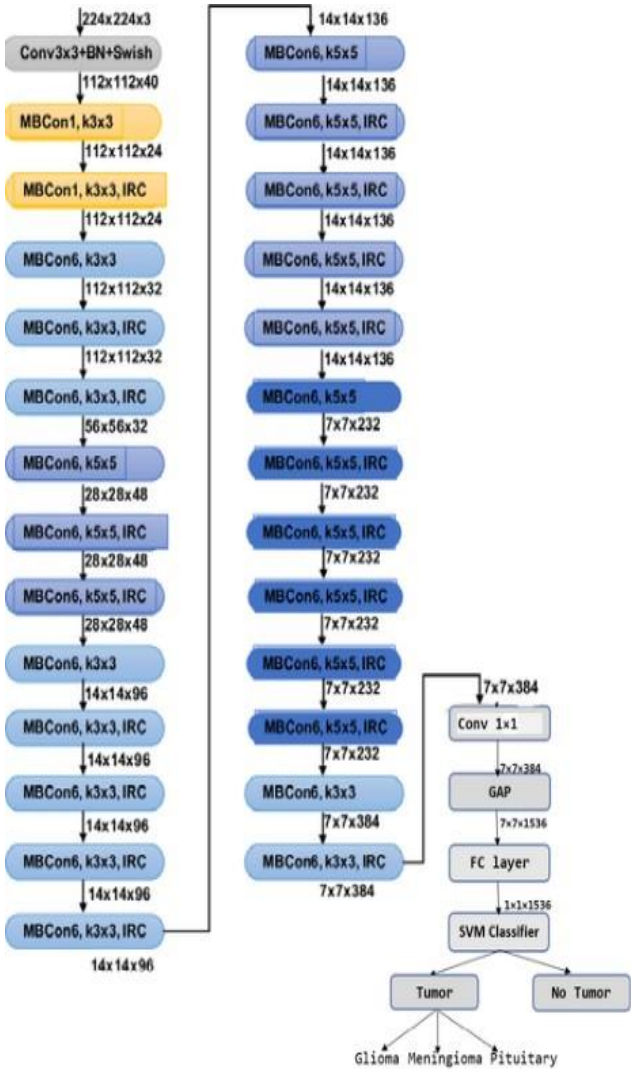

Fig. 3. **Architecture of proposed hybrid model (EfficientNet B3+SVM)**

Fully Connected Layers: The feature vector is input into a fully connected layer that has 1536 hidden units and uses a ReLU activation function. After this layer, there is a dropout layer and then a final output layer with the number of units equal to the number of classes in the dataset.

IV. RESULT AND SIMULATION

To provide error-free diagnosis and classification of brain tumor. We have taken 7023 two- dimensional MRI images from the Sartaj and ImageNet dataset. These are resized to a uniform dimension of 300x300x3. provide as an input dataset to the model. These are fractionated into four prejudiced categories. Three of them were found to have tumors and no tumor was found in one. These categories are the following:- glioma, meningioma , pituitary tumor and no tumor. The weighted dataset was manufactured in

the course of the training phase. It is then split into 80% for training (5712 MRI images) and 20% for testing (1311 MRI images). The dataset must be stabilized in the course of the training phases, but that was not automatically in the course of the testing phase. We have evaluated the performance of the hybrid model that is (EfficientNet B3 and SVM classifier model). The hybrid model provided 99% accuracy. The comparison of the accuracyof our model with the existing model is listed in the table II.

TABLE II
THIS MODEL (EFFICIENTNET B3 + SVM) PROVIDE BETTER ACCURACY AS COMPARED TO ALL OTHER MODELS WHICH IS 99%.

S.No.	MODEL	ACCURACY
1.	VGG 16	98.69%
2.	DarkNet-53	98.54%
3.	Inception V3	75%
4.	ResNet 50	95%
5.	AlexNet	91%
6.	ResNet 50+SVM	91.20%
7.	AlexNe+SVM	95.10%
8.	**EfficientNet B3+SVM (Our Model)**	**99.0%**

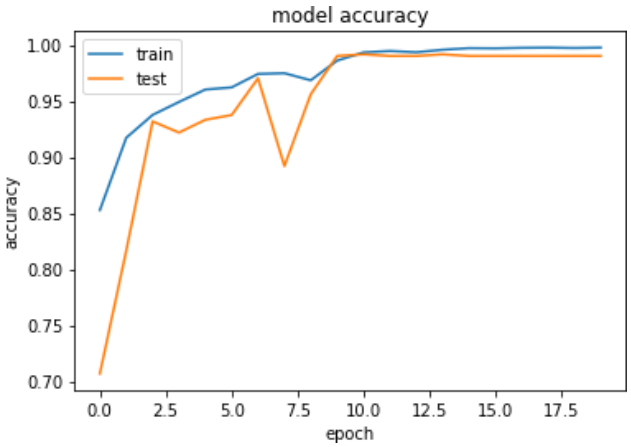

Fig. 4. **Model Accuracy** a.) Training accuracy is 0.99. b.) Testing accuracyis 0.98

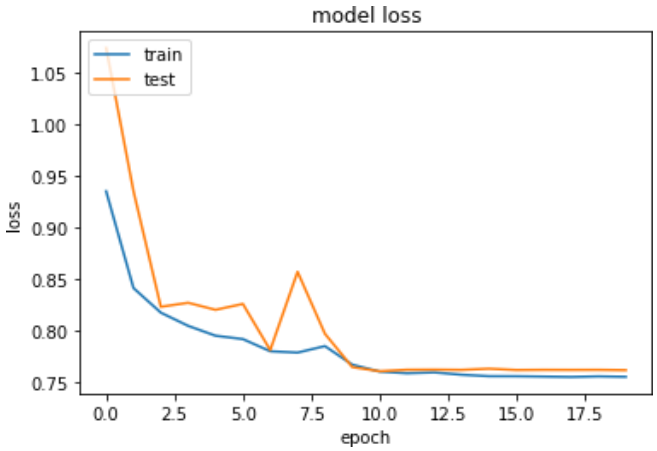

Fig. 5. **Model Loss** a.) Training loss is 0.75 b.) Testing loss is 0.76

IV. CONCLUSION

Brain tumors are abnormal aggregates of cells that proliferate and multiply out of control in the brain, obviously unfettered by the procedure that overcome typical cells. Approximately, above 160 various brain tumors have been certified. The brain tumors are conception to originate when definite genes on the chromosomes of a cells are injured and extinct task appropriately. The brain tumor is a capable of causing someone's death complications and drawbacks and usual working of the human body. For accurate identification and systematic preparation, it is mandatory to locate the brain tumor in initial levels. By initial brain tumor detection,the patient gets the right treatment as soon as possible , which improves the patient's survival chances. Firstly, braintumor is diagnosed by Magnetic resonance imaging (MRI) tests with enlargement of AI methods. Darknet model used for complete classification of brain tumor. In this work,it was found that hybrid model using a pre-trained CNN (Convolutional Neural Network) and SVM (Support Vector Machine) gave the most accurate value for the execution of brain tumor classification. We have make new model by replacing the output layer of the EfficientNet B3 architecture with the SVM classifier layer which provide better accuracy. In the comparison of other model which are listed inthe table II, our model gave best accuracy result.

In the coming times, super resolution will be applied in this model to classify brain tumors and to check the accuracy of the model will be increased or not.

IV. DATASET DESCRIPTION

The dataset are taken from the kaggle which are uploaded by the SARTAJ group. This dataset includes 7023 MRI scans of the human brain that have been divided into 4 classes: meningioma, pituitary, glioma, and no tumor.

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