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An Efficient Pre-Trained Classification of Brain Tumor with Convolutional Neural Networks

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Abstract **—One of the deadliest malignancies in the world, brain tumors are caused by the brain's cells growing unnaturally. The stage at which the cancer is discovered affects the disease's survival rate. In order to increase the survival probability through effective treatment regimens, it is crucial to precisely identify the tumor area in the brain as well as the tumor type as initial as feasible. The use of magnetic resonance imaging of the patient as being among the primary methods for analysing the tumor is one of the most essential aspects of this process. The vast amount of data being created makes manual procedures ineffective and prone to classification errors. Performing a manual analysis of the magnetic resonance imaging (MRI) pictures might be difficult. As a result, there is a need for computerised methods to tumor diagnosis that are more accurate. Nevertheless, establishing their volume, form, boundaries, size, segmentation, and categorization continues to be a process that is fraught with difficulty. The study comprises two parts: first, an experimental exploration of brain MRI images that concentrates on specific features, and second, a comparative analysis of multiple transfer learning models based on convolutional neural networks (CNNs) for the purpose of classifying brain tumors. Using MRI images of the brain, it reveals how successful deep knowledge approaches may be in the detection of brain cancer. Performance is determined based on how accurately training and testing are carried out. In this instance, a numeric classifier is used, with the classifications no tumors and tumors. Using a range of methods integrating medicinal copy dispensation and artificial idea for improvement, division, and cataloging of brain finding, the goal of our research is to properly identify and categories brain tumors.**

Keywords—GBF, Otsu's Threshold method, GLCM, BWARD, CNN, VGG16, EfficientNetBO

I. Introduction

Brain tumors are regarded as a fatal condition that affects many people's lives worldwide. The World Health Organization (WHO) notes that in 2016, the tumors are classified as low-grade (LG) and high-grade (HG) glioblastomas and gliomatumors, respectively. A benign tumor, commonly referred to as a low-grade tumor, does not significantly harm surround healthy tissues. A malignant tumor, on the other hand, is the exact opposite of a benign tumor; in this case, the tumor cells directly cause the person's death and they are known as high-grade tumors. They are also quickly spread through the surrounding brain tissues. Thus, scanning techniques are castoff to detect tumor cells in the brain earlier in order to avert this fatal occurrence. Excellent resolution, complex soft tissue distinction, and improved contrast are only some of the MRI image processing technologies that may be used to cope with the features of the human brain. [4].

When it comes to monitoring oncologic treatment, one of the most important responsibilities is the accurate and morphological quantification of tumors Popular which the brain tumor is segmented after the MRI pictures have been analyzed. Several image segmentation techniques have been used to separate this malignancy.

Researchers have developed a variety of ways for identifying brain tumors, but because the brain is so complex, these methods still fall short in terms of accuracy. These essential factors served as our inspiration for doing this investigation[5]. The GBF filter is employed for pre-processing to improve the value of the brain image in instruction to get around these problems. These in-depth features can reveal information about the various tumor kinds and are very discriminative. The majority of cancers may now be found early on thanks to the development of scientific theories and imaging technology. This study investigates deep learning methods for MRI-based tumor applications[6].

The subsequent is a list among the most important contributions made by this suggested methodology:

- An upgraded guided bilateral filter (GBF) is used in the pre-processing period to reduce sound and blurring. A GLCM technique is also used to extract features.
- To choose the best features, the (BWARD) algorithm is presented.
- To effectively cluster data for the segmentation procedure, Otsu's Threshold approach is employed.
- In order to classify brain tumors as either normal, benign, or malignant with high accuracy, Convolutional Neural Network (CNN), VGG16, and EfficientNetB0 were utilized. The study is divided into five sections, beginning with a literature review in Section 2, followed by a description of the proposed method in Section 3. Section 4 presents the results and discusses their implications, while Section 5 provides a general conclusion.

II. Literature Review

In this literature, various number of sensor-based wearable health monitoring devices in machine learning with edge has been suggested. Several studies have been developed to use MRI scans to diagnose brain cancer. Many studies were studied, and the methodologies and datasets used were examined. Despite the fact that common datasets were used in numerous analyses, distinct results were

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obtained. The primary reason for this is because the parameters differ even when the same process is used. In one study, existing models were altered and theclassification technique was carried out. Greater accuracy rates were sought in this manner.

he creation of CAD tools for tumor grading using multiple medical imaging modalities is a burgeoning field of study.MRI is the research method of choice in this situation. The main stages involved in CAD tools are preprocessing, segmentation, feature extraction, and classification. Feature selection is a crucial aspect of these tools. AI techniques can be divided into two categories based on feature selection: Machine Learning (ML) and Deep Learning (DL). In classical ML models, features are manually defined and known as "handcrafted features". The characteristics are automatically extracted from the photos in the case of the DL approaches, however, during training. This is a summary of a few of the classic ML-based research for classifying brain tumors.

The image denoising becomes more costly and less reliable as the patient population and the quantity of data that has to be analysed each day continues to grow. A visual issue is presented to the spectator as a result of a number of different characteristics, including the form, dimensions, difference, and high changes with regard to the intensity of the tumor. This necessitates the development of a computer-aided diagnostic (CAD) system that may provide radiologists and medical professionals with further support [7].

It is possible for a computer assisted diagnosis (CAD) program to be an efficient tool that can readily categorise brain tumors, which may aid in successfully following a treatment protocol. The MRI pictures may be obtained from the MRI equipment by such a system as the initial stage in the process. In current history, a number of scientists have suggested and created a variety of automated classification techniques for brain tumors using MRI data. In 2013, Sach deva and colleagues created a computer-aided diagnosis (CAD) system that encompassed picture segmentation, the extraction of features, and the multiclass categorization of six different types of brain cancers. The total quality of classification was found to be 85% [8], which was determined by carrying out three separate tests deploying artificial neural networks.

Emre et al. classified benign and malignant tumors using a procedure called support vector machine (SVM), which is a machine learning approach. With an effectiveness of 91.49%, a sensitivity of 90.79%, and a specificity of 94.74%, this method was able to describe the brain tumors. [9].

The overlap index parameter and Jaccard coefficient are employed to compare the results with manually segmented ground truth ROI images derived from the original images. Praveen and Agrawal proposed a multistage method that involves image preparation processes, feature extraction using histogram and GLCM approaches, and classification using a random forest (RF) classifier. Prior to the categorization process, it is critical to extract relevant components from the available data. To isolate the tumor from segmented brain images, the authors utilized circularity and area characteristics. The authors achieved an average overlap of 72.9% when comparing their segmented images with ground truth images to verify their methodology. In contrast, deep learning, a type of machine learning that does not require the subjective extraction of features, was used to achieve an accuracy of 91.43% in this study.

The latest advancement in machine learning involves enabling computers to recognize the most significant characteristics that accurately capture the data. Deep neural networks, such as the Convolutional Neural Networks (CNN) and Fully Convolutional Networks (FCN), have emerged from thisconcept, which transforms feature-driven problems into data- driven ones. These deep neural networks have found applications in a wide range of areas.

They are specifically employed in medical image analysis as well as general image processing in today's society. Brain Tumor Imaging (BTI) has increased significantly during the past few decades. In particular, there has been a notable rise in the quantity of publications addressing the measurement of brain tumors using MRI scans. Differentiating between tumor-infected and healthy tissues is the goal of brain tumor segmentation (BTS).

The approach of pixel classification is utilized to address the segmentation problem in various brain tumor segmentation (BTS) applications, thereby converting the segmentation problem into a classification problem, ultimately leading to the successful segmentation of brain tumor images. The majority of the academics make use of the benchmark dataset known as Brats 2013. In subsequent years, a number of other categorization schemes for brain tumors based on CNN were presented. Meningiomas, Gliomas, and Pituitary Cancers Were Identified Using One Approach This specific system classified all three kinds of tumors, which resulted in a classification accuracy of 97.3% [12].

Following an assessment of existing systems, it was discovered that there are various research gaps that have yet to be filled. Because brain tumor categorization is one of the more challenging study topics, numerous successful strategies must be combined to generate superior prediction results. However, the time complexity is significantly increased, which decreases overall performance. One challenge is that complex models are computationally inefficient, and models require a substantial amount of input data to yield improved outcomes. To address all research gaps and achieve superior classification results, a new deep learning methodology is introduced in this study. By incorporating more distinct input features, the proposed approach achieves higher accuracy rates.

III. Methodology

The purpose of the future research is to improve the efficiency of the operation of traditional classifiers. These classification methods are useful for computer aided brain tumor identification and classification because they need minimum datasets for training as well as a reduced computational complexity of the algorithm. This makes it possible for the computer to identify and classify brain tumors.

When it comes to detection, we advise utilising a Convolutional Neural Network (CNN), namely VGG16 and EfficientNetB0. To differentiate between benign and malignant brain tumors, it is essential to determine the extent of the tumor-affected region. Otsu's threshold approach is initially applied during the segmentation process for MRI images. Gray-Level Co-Occurrence Matrix approaches (GLCM) are utilized for feature extraction, resulting in thirteen characteristics that can be utilized for classification (11). During the course of the present study project, we have investigated the studies of a number of different classifiers, such as CNN, VGG16, and EfficientNet Classifier. In general, it worked to improve performance by using traditional classifiers wherever possible. The functioning of the new implementation that has been suggested is shown in figure 1.

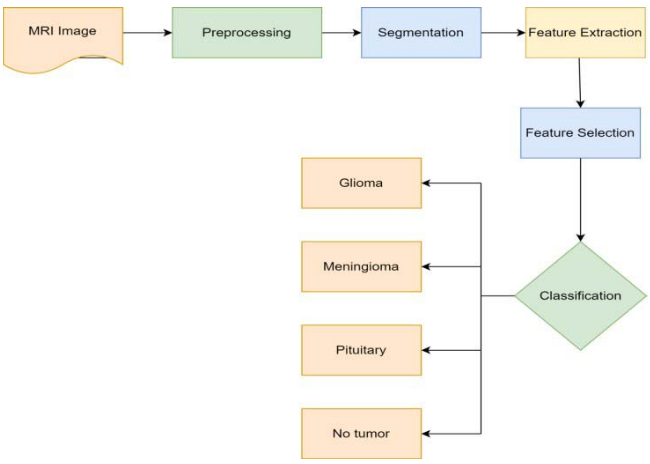

Fig. 1.Process Flow

3.1 *Pre-processing*

Several preprocessing techniques are used to decrease the impact of the noise and blurring. The multiple processes decide whether measurements are of greater quality. In the suggested approach, the GBF (Guided bilateral filter) is a technique used in image processing to enhance the visibility of certain features by removing noise and other unwanted frequencies in the image. It works by convolving the image with a Gaussian kernel, which acts as a filter to pass through only a certain range of frequencies, while attenuating others. This can be useful for tasks such as edge detection and feature extraction. The process of preprocessing an image using a GBF filter involves applying the filter to the image before performing any other image processing tasks.

3.2 *Segmentation*

Segmenting brain tumors using Otsu's thresholding method can be a useful technique. The following steps can be used:

1. Convert the MRI scan to a grayscale image.
2. Preprocess the image by removing noise and other unwanted artifacts using techniques such as Gaussian smoothing or median filtering.
3. Compute the histogram of the grayscale image and find the optimal threshold value using Otsu's method.
4. Apply the threshold value to the image by setting all pixels with an intensity value greater than or equal to the threshold to 255 (white) and all pixels with an intensity value less than the threshold to 0 (black). This creates a binary image with the tumor as white and the healthy brain tissue as black.

It is significant to note that Otsu's thresholding method may not be the best choice for all brain tumor images. It works best for images with bimodal histograms, where the brain tissue and tumor pixels have distinct intensity values. In cases where the histogram is not bimodal, other methods such as adaptive thresholding or region-based methods may be more suitable.

3.3 *Feature extraction using GLCM methods:*

The image processing technique known as GLCM (Gray- Level Co-occurrence Matrix) is used to extract texture information from a picture. The following steps can be used for feature extraction using GLCM methods in brain tumor images:

1. Convert the brain tumor MRI scan to a grayscale image.
2. The grayscale image can be partitioned into smaller regions of interest (ROIs), such as the tumor and the surrounding brain tissue.
3. For each ROI, compute the GLCM by counting the number of times different gray-level values appear in pairs in a specified spatial relationship (e.g., 0, 45, 90, or 135 degrees).
4. Extract texture features from the GLCM.
5. Compare the texture features of the tumor ROI to those of the surrounding brain tissue to identify any significant differences.
6. Utilize the extracted characteristics as input for a classifier, such as Support Vector Machine (SVM), to categorize the ROIs as either tumor or healthy brain tissue.

3.4 *Feature selection*

In the proposed framework, the fourth module involves feature selection, wherein significant characteristics are extracted while insignificant ones are discarded. The fundamental purpose of the feature selection process is to reduce the computational complexity overall by minimising the dimensionality problem. The suggested framework uses a hybrid optimization approach based on meta-heuristics to choose the best features. This paper suggests a new BWARD algorithm to choose the pertinent features and improve classification precision

3.5 *Classification*

3.5.1 *CNN-Based Architectures*

A CNN convolution layer is a kind of system that combines an image with several filters in order to generate feature maps. These feature plots are then sent on to the subsequent complication sheet in order to remove an additional high-level component from the input picture. Within the difficulty sheets, non-linearity equations, in

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conjunction with a down cast probability sampling, are used to accomplish the goals of adding non-linearity to the picture as well as reducing the image's complexity [13]

3.5.2 VGGNet

Some other CNN architecture that also was developed in 2014 was called VGGNet16. This design finished in second position in the competition on the basis of correctness, but it took the top spot in the ILSVRC. All completely linked layers use the ReLU activation function, while fully connected layers employ dropout regularisation.Compared to AlexNet and GoogleNet, the CNN model is computationally more expensive because of the high number of parameters.[13]

3.5.2 Efficient NetworkBO

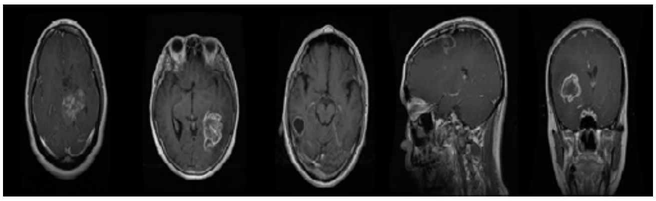
A technique for scaling CNN's depth, width, and resolution is called an efficient network. From EfficientNet-B0 through EfficientNet-7, there are eight categories in the Efficient network. To enhance the overall performance model, Efficient Network scales using a defined and consistent set of coefficients. An example of compound scaling from the baselinenetwork is shown in Figure 3.[14]

IV. DATASET COLLECTION AND DESCRIPTION

The Kaggle database's brain tumor dataset includes 2659 T1- weighted, contrast-enhanced pictures. The dataset includes three different kinds of brain tumors: glioma (927), meningioma (373), pituitary (926), and no tumor (433).The files were all saved in.jpg format. Table 1 and image 3 provide MRI dataset samples of glioma, meningioma, and pituitary tumors.

TABLE 1:REPRESENTATION OF MRI DATASET

	Glioma	**Meningioma**	**Pituitary Tumors**	**No Tumors**	**Total No. Of Samples**
Training samples	826	245	827	328	2226
Testing samples	101	128	99	105	433



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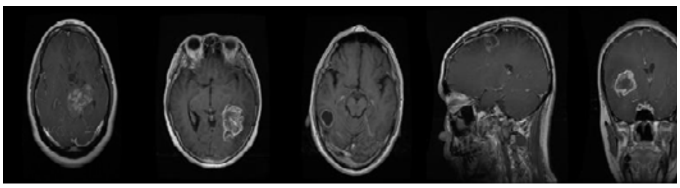

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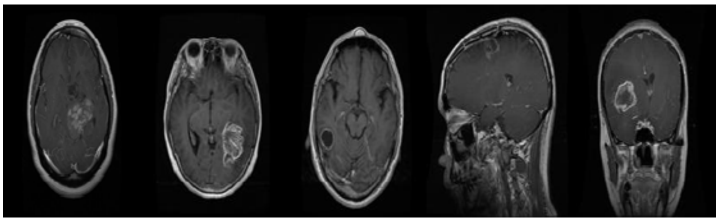

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Figure 2. MRIDataset Samples of Glioma, Meningioma and Pituitary Tumour

V. RESULTS AND DISCUSSION

Edge Metrics and evaluation of performance a classifier's performance can be assessed using a variety of defined performance indicators. The quality index that is most frequently employed is classification accuracy. The proportion of samples that were correctly classified to all samples of data is known as accuracy in classification. The following classification accuracy results were attained in our tests. On the training set, CNN achieves an accuracy of 99.38%, while on the testing set, it only achieves an accuracy of 73.35%. With VGG16, the training set accuracy is 84.75 percent, however the testing set accuracy is just 53.30 percent. For EfficientNetB0, the accurateness on working out set is 99.46%, but the correctness on testing set is 74.37%.

The data shows that using CNN, VGG16, EfficientNetBO to categories the deep CNN features results in better performance. Nevertheless, the dataset that was utilized for the classification issue that was being discussed is not consistent. Because of this, the recommended system has to be evaluated in a more comprehensive manner, making use of additional performance metrics. We made use of confusion matrices in order to assess the efficacy of the system we developed for classifying tumors.

Evaluation Metrics

The efficiency of the suggested system for classifying and detecting brain tumors is assessed by calculating assessment metrics based on the four primary outcomes that are employed and to calculate a test's accuracy, Using the following equations, we determine the total number of instances that were examined and the number of cases that yielded true positive and true negative results:

$$\text{Accuracy} \quad \frac{TP+FN}{TP+TN+FP+FN} \qquad (1)$$

Sensitivity is a measurement of a system's capacity to properly categorise brain tumors. It is derived from the percentage of cases in which the diagnosis was correct by using the following relation:

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

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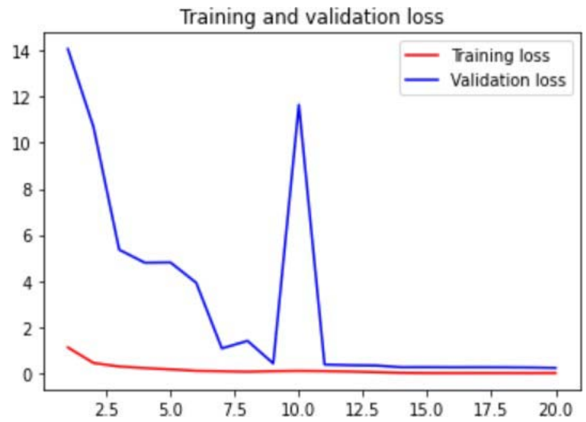
The capacity of the modeling to correctly identify the real kind of brain tumor is referred to as particular, and itmay be calculated as follows

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

Precision is the true positive measure and is computed using relation:

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (4)$$



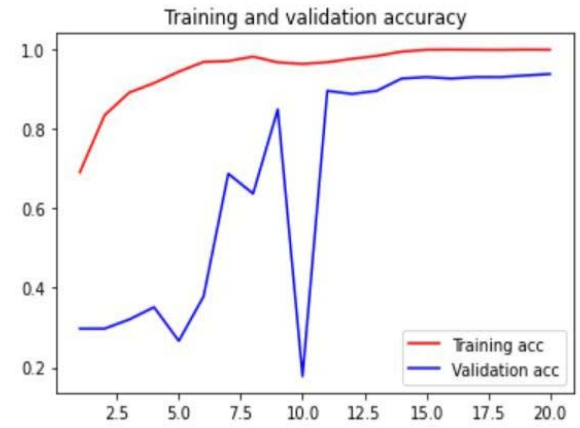


Figure 3.Validation accuracy and loss (CNN)

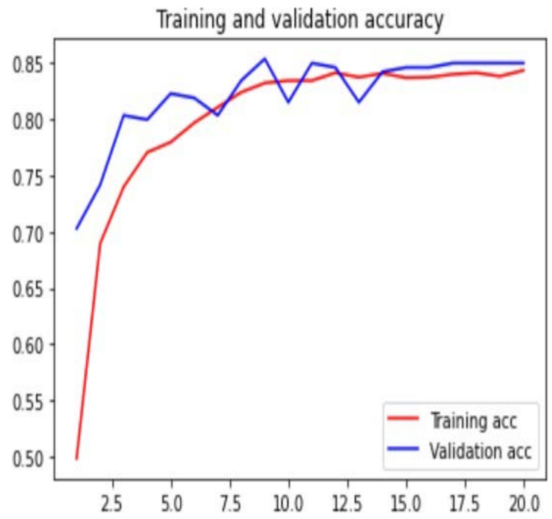


Figure 4.Validation accuracy and loss(VGG 16)

TABLE 2: CLASSIFICATION REPORT FOR CNN

	P	R	F1-score	support
0	**0.76**	**0.16**	**0.26**	**100**
1	**0.76**	**0.95**	**0.84**	**115**
2	**0.65**	**0.99**	**0.78**	**105**
3	**0.87**	**0.81**	**0.84**	**74**
Accuracy	**-**	**-**	**0.73**	**394**
Macro avg	**0.76**	**0.73**	**0.68**	**394**
Weightedavg	**0.75**	**0.73**	**0.68**	**394**

The effectiveness on the training collection for the VGG16 model is 84.75%, however the consistency on the validation set is just 53.30%.

TABLE 3: CLASSIFICATION REPORT FOR VGG 16

	P	R	F1-score	support
0	**0.42**	**0.18**	**0.25**	**100**
1	**0.53**	**0.59**	**0.56**	**115**
2	**0.49**	**0.69**	**0.57**	**105**
3	**0.69**	**0.70**	**0.70**	**74**
Accuracy	**-**	**-**	**0.53**	**394**
Macro avg	**0.53**	**0.54**	**0.52**	**394**
Weighted avg	**0.52**	**0.53**	**0.51**	**394**

The accuracy on the training set for EfficientNetB0 is 99.46%, whereas the effectiveness on the validation set is just 74.37%.

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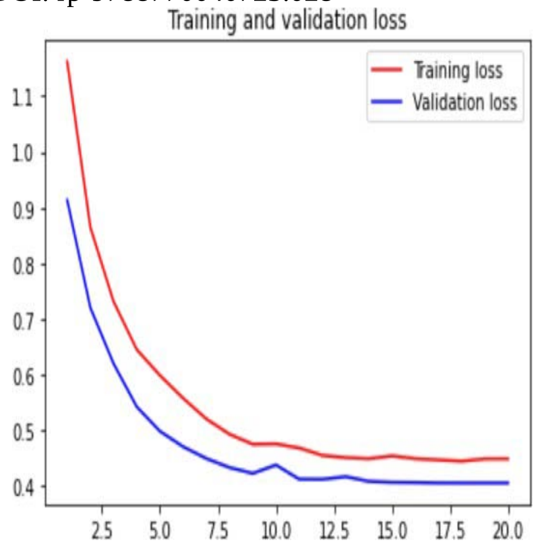

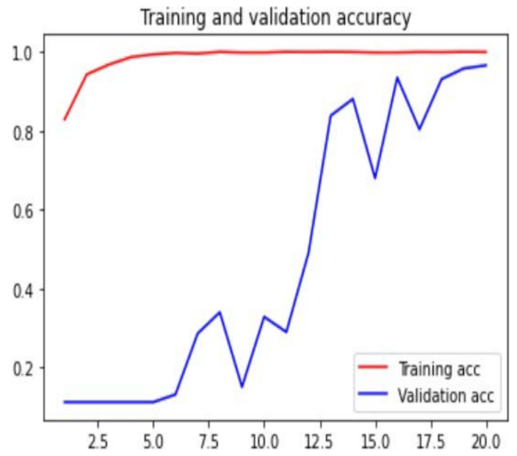

TABLE 4: CLASSIFICATION REPORT FOR EFFICIENTNETBO

	p	re	F1-score	support
0	**0.96**	**0.27**	**0.42**	**100**
1	**0.72**	**0.97**	**0.82**	**115**
2	**0.65**	**1.00**	**0.79**	**105**
3	**1.00**	**0.68**	**0.81**	**74**
Accuracy	**-**	**-**	**0.74**	**394**
Macro avg	**0.83**	**0.73**	**0.71**	**393.5**
Weightedavg	**0.82**	**0.74**	**0.71**	**393.5**

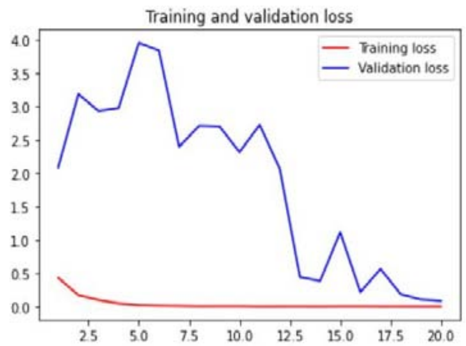

Fig 5.Validation accuracy and loss(EfficientNetBO)

By contrasting the suggested CNN classifier model with earlier neural network techniques, he model's efficacy was assessed. Table 1 displays the performance comparison. With a training accuracy of 99.85% and a testing accuracy of 78.93%, the recommended method outperforms the earlier developed methods.

TABLE 5. REASONABLE INVESTIGATION OF CLASSIFICATION ACCURACIES

Model	Train	Test
CNN	**99.38%**	**73.35%**
VGG16	**84.75%**	**53.30%**
EfficientNetBO	**99.46%**	**74.37%**

VI. CONCLUSION

The proposed study aims to develop an effective deep learning- based brain tumor classification model that provides accurate tumor categorization. The model consists of five primary modules: pre-processing, segmentation, feature extraction, feature selection, and classification. Initially, the MRI images are pre-processed using the GBF filtering approach, and then the tumor regions are extracted using the Otsusthresholding technique. Key texture and edge features are retrieved from the images using the GLCM technique, and the extracted features are reduced using the BWARD algorithm to address dimensionality concerns during classification. Finally, the proposed CNN model categorizes the input features into four categories: glioma, meningioma, no-tumor, or pituitary tumor. Through simulations, the model achieves an overall accuracy of 99.46% on the brain tumor MRI dataset.

In the future, new types of MRI images, such as multi-modal imaging, will be explored to provide more informative classifications. Furthermore, new and hybrid deep learning models will be investigated to deliver more accurate categorization results. In addition to brain tumor classification, there are several other crucial diseases in need of a classification model, and it is expected that these disorders will be prioritized in the near future to reduce mortality rates and improve treatment techniques.

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