e-Prime - Advances in Electrical Engineering, Electronics and Energy 8 (2024) 100498

Contents lists available at ScienceDirect

e-Prime - Advances in Electrical Engineering, Electronics and Energy

journal homepage: www.elsevier.com/locate/prime

# Multigrade brain tumor classification in MRI images using Fine tuned efficientnet

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ARTICLE INFO

*Keywords:*
Convolutional Neural Network
Grad-Cam
Deep Learning
Transfer learning

ABSTRACT

Medical imaging plays a vital role in detecting and treating brain tumors. Malignant or non-malignant brain tissue's abnormal growth causes long-term brain damage. It is crucial to detect and properly categorize the kind of brain tumor. Specialists normally use MRI to create high-contrast grayscale brain images to segment them. Convolutional neural networks (CNN) driven by deep learning (DL) have transformed computer-assisted testing systems by producing good results in a wide range of medical imaging analytics applications, including tumor diagnosis in the brain. The paper introduces a lightweight fine-tuned Convolutional Neural Network EfficientNet 'ECNN' to detect brain tumors. In this study, we provide a transfer learning-based measurement strategy for grouping cerebrum growths in three distinct datasets with different classifications, such as meningioma, glioma, and pituitary growth, using fine-tuned EfficientNets. The findings of this research rely on Efficient Nets to classify brain tumors in three different types of datasets utilizing a fine-tuned transfer learning mechanism. With EfficientNetV2S as the system's foundation, our proposed way of fine-tunned pre-trained EfficientNetV2S model outperformed for all datasets over state of the art methods. The effectiveness of the suggested model has been assessed using performance metrics, and outcomes were compared to those produced using state-of-the-art approaches. The average test accuracy, recall, precision, and sensitivity score are 98.48%, 98%, 98.5%, and 98.71%, respectively.

## 1. Introduction

Today, brain tumors have become a leading cause of death worldwide with 2-3 million deaths annually, as per the report of the World Health Organization. This is the main cause of some acute problems such as muscle weakness, amnesia, paralysis, etc and the result is death in the majority of cases. The brain is a major part of our body that plays a significant role and controls all the functionality of our nervous system by connecting a large number of neurons. Rapid and aberrant growth of normally developing neural structures is a symptom of brain tumors. Nearly 4 lakh people were affected by brain tumors and amongst them, about 1-2 lakh deaths occurred due to the severity of the disease as per past records provided by the World Health Organization (WHO) [1]. Along with surgical removal, chemotherapy and radiotherapy may be needed in a few cases to treat such brain tumors. Due to the aggressive nature of this disease, it has the highest mortality rate in the world and is considered the 10th most affected disease worldwide. As a result, early diagnosis of brain tumors is essential for people's lives so that suitable medical care may be provided at the appropriate time. Four grades are used to classify these tumors. Grade I and II are slow-growing tumors, but Grade III and IV are extremely aggressive and more likely to spread [2]. A tumor can occur anywhere in body parts but majorly occurs in the brain. Again brain tumors can be categorized according to the origin as primary or secondary. Primary tumors develop from the primary brain tissues and secondary tumors spread from other organs of the body such as the lungs, colon, breasts, skin, etc. in a process called metastasis and migrate toward the brain. As per the embryological origin of neural tissues brain tumors can be classified as Glioma, Meningioma, Schwanoma, Pituitary tumors, etc. Glioma arises from the glial tissues of the brain. Out of all the primary tumors, Glioma has a higher morbidity and mortality rate. Similarly, Meningioma tumors arise from brain meninges and spinal cord. Pituitary tumors develop from abnormal and uncontrolled growth of the pituitary gland which is a main source of hormones controlling the entire endocrine system of the human body. The two main forms of glioma tumors are low-grade glioma and high-grade glioma [4]. Different imaging techniques have been used to visualize the

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https://doi.org/10.1016/j.prime.2024.100498
Received 14 November 2023; Received in revised form 10 February 2024; Accepted 5 March 2024
Available online 12 March 2024
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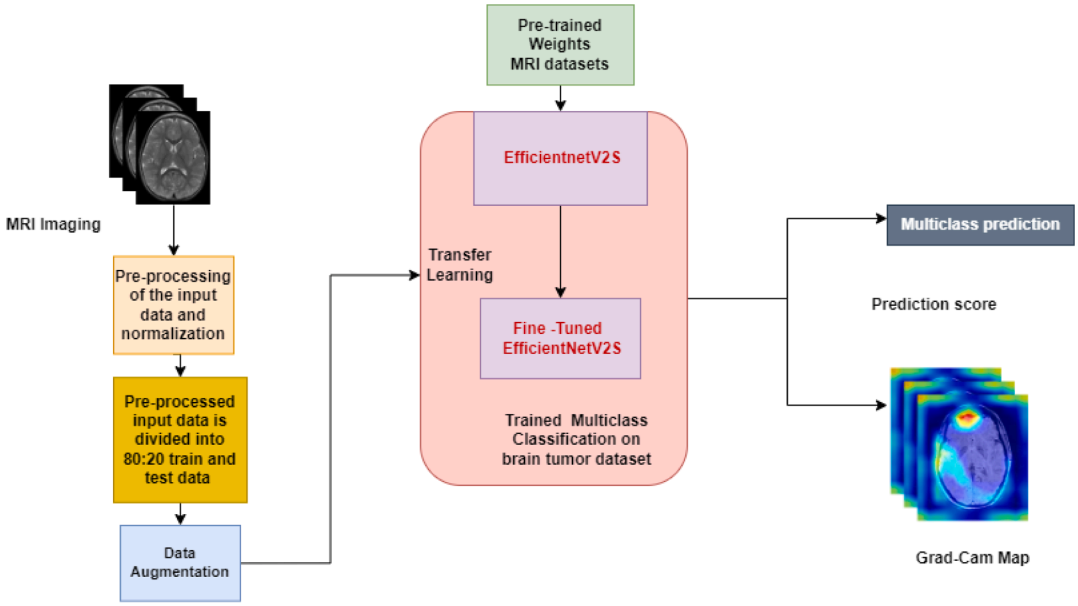


**Fig. 1.** The proposed framework for brain tumor detection using Grad-CAM visualization mechanism and transfer learning technique.

**Algorithm 1**
Step-wise procedure for Data Augmentation in ECNN Model.

1.# Load Dataset (Ld($n$))
2. Split Dataset (Sp($n$)) into three parts: test (nt), training (ntr), and validation (nv) Create a list of class labels based on the sub-folders present in a directory
3.$Sp(n) = Sp(nt, ntr, nv)$
4. Get Original Image ($Sp(no)$)
5.Shuffling the training data arrays to randomize the order of the training data($Sp(noSh)$)
6. Transform the categorical data using a label encoder ($Sp(Ci)$)
**for all** images in $Sp(Ci)$ **do** ▷ Loop for all images
    Apply steps (iii)
**end for**
7. Resize Images ($Sz(Cn)$) to $240 \times 240$ pixels
8. Apply Augmentation ($Ag\{Sz(Cn)\}$) for all images

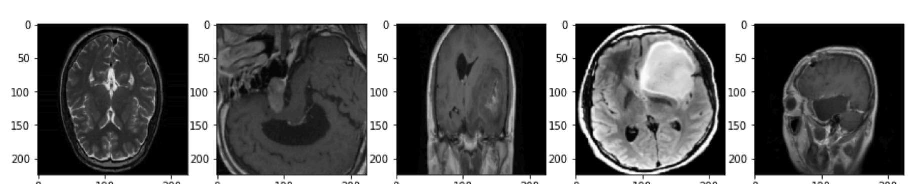

**Fig. 2.** Sample augmented images.

exact location of brain tumors such as MRI, CT, PET, and X-rays. The midst of MRI is a non-invasive device with non-ionizing effects for tumor detection. MRI brain image provides better anatomical and morphological information about the nervous system. MR imaging is a very popular visualization technique that is non-invasive and can visualize better contrast of the soft tissues and also it has the accessibility of multispectral images [5]. The manual detection method is a time-consuming task. Therefore, it is very essential to design an automatic computer-aided diagnosis system that will be helpful for radiologists to make quicker and more accurate decisions. In the present day, machine learning-based approaches are very essential and it is so designed to detect various stages of the tumor present in the brain and inform the complexity of the patients earlier so that the patient gets alert based on the infection. This work aims to classify T2- weighted MR images into normal or abnormal images. Artificial intelligence and machine learning have become more prominent and have a huge role in

**Table 1**
Parameter setting in data augmentation.

| Augmentation type | Value |
|---|---|
| Rescaling | $\frac{1}{.255}$ |
| Rotation range | 7 |
| Width shift range | 0.05 |
| Height shift range | 0.05 |
| zoom range | 0.1 |
| Horizontal flip | True |
| Additional rotation | 0,90,180 |

the medical industry recently. Using different machine learning models, we can predict and diagnose the disease class at the right time. However, the selection of the most efficient classifiers using machine learning (ML) is one of the most challenging tasks for designing a system. Creating a reliable and accurate system to divide brain tumors into several grades using data taken from MRI scans is the problem statement for the multigrade brain tumor classification in MRI images. The objective is to develop a trustworthy classification model that can identify between various tumor grades, which is crucial for supporting medical practitioners in their decision-making and treatment planning. The model's generalizability to a variety of patient populations and imaging conditions, handling the complex and varied nature of brain

**Algorithm 2**
Proposed Fine Tuned EfficientNetV2S model for Multigrade Brain tumor Classification.

1. **ImportEfficientNetV2S** ← #Load EfficientnetV2S()

2. **Define custom model for transfer learning**
$custom\_model \leftarrow EfficientNetV2$
3. **Edit the custom model last layer(transfer learning(add04layers)** $custom\_model \leftarrow custom\_model + GAP + L(Dropoutlayer(0.3) + Flatten + Dropout(0.2) + Dense) + ApplyAct.(ELU) + ApplyAct.(Softmax) + ApplyAdamOptimizer$
4. **Generate training dataset**
5. **Initialize training parameters** $Epochs \leftarrow 25$ $Batch\_size \leftarrow 5$ $ValidationSteps \leftarrow 50$
6. **Train the model**
$Mt \leftarrow TrainModel(custom\_model, Epochs, Batch\_size)$
7. **Generate and plot model accuracy and loss graphs**
$MAcc \leftarrow GetModelAccuracy(Mt)$
$MLoss \leftarrow GetModelLoss(Mt)$
$PlotModelMetrics(MAcc, MLoss)$
8. **Generate confusion matrix**
$ConfMatrix \leftarrow ComputeConfMatrix(Mt)$
9. **Find the accuracy of the model**

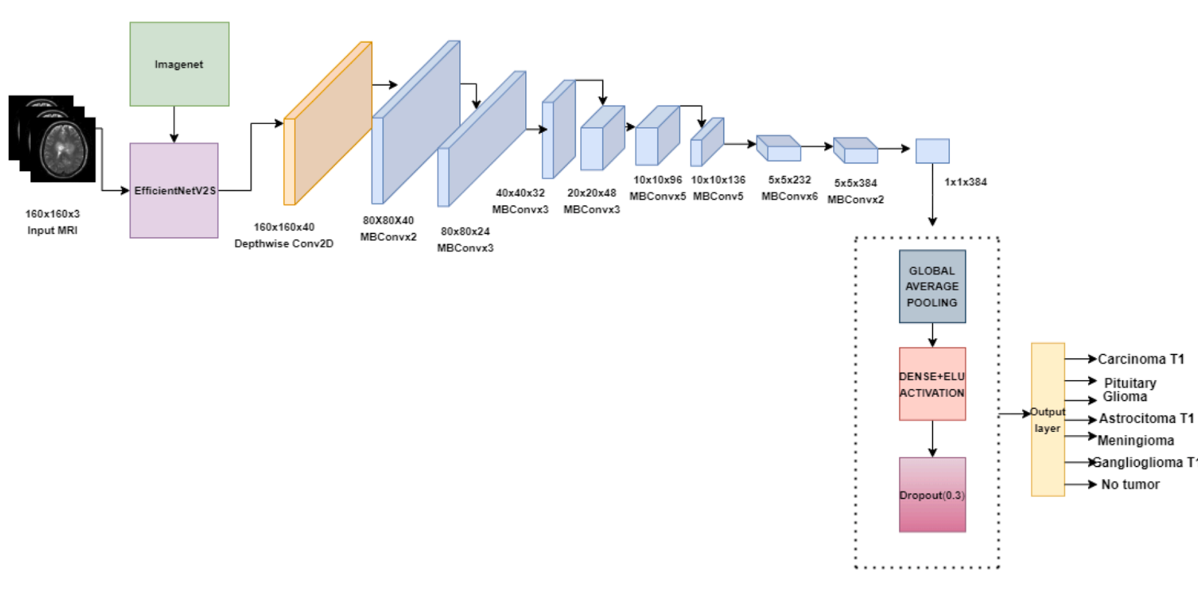


Fig. 3. Block diagram of the proposed fine-tuned ECNN model.

**Table 2**
An outline of the studies on brain tumor identification utilizing Machine learning and Deep learning methods.

| Author | Technique | Datasets | Acc% |
|---|---|---|---|
| Our method | EfficientNetV2S | 3064 T1 | 98.5% |
| Sajjad et al. [2] | Input Cascaded CNN, VGG-19 | Radiopaedia 121 MR images | 90.67% |
| Kibriya et al. [4] | A light weight CNN model | Figshare | 97.2 % |
| Swati et al. [28] | Pre-trained VGG-19 | CE MRI | 94.82% |
| Nayak et al. [29] | SFOA,FBIA,MGA metaheuristic approach | Kaggle datset 3 classes | 98% |
| Kaur et al. [5] | Inception v3,Resnet101 | Harvard, figshare, benchmark | 98%, 94%, 95.92% |
| Pundir et al. [14] | VGG16 | Public datasets | 91.8% |
| Rabab et al. [20] | B-PSO,ACO,ABCO | Radiopedia dataset | 88 % and 94% |
| Deepak et al. [21] | GoogleNet | datasets | 97% |
| Jayaprada et al. [22] | Adaboost algorithm | Kaggle datasets | 90.4% |
| Cheng et al. [26] | GLCM,BoW method | public datasets | 91.28% |

**Table 3**
Description of Dataset.

| Dataset | Training images | Testing images | Classes |
|---|---|---|---|
| Dataset-1 | 3998 | 788 | 4 |
| Dataset-2 | 3246 | 293 | 12 |
| Dataset-3 | 3584 | 895 | 44 |

tumors, and achieving high accuracy in classification across multiple grades are among the challenges. To improve diagnostic accuracy and patient outcomes, the ultimate goal of this research paper is to advance the field of medical image analysis by developing cutting-edge CNN and deep learning models for multigrade brain tumor classification in MRI images.

Medical imaging has provided many advanced imaging tools for clinical diagnosis in a better way. Many well-known ML algorithms were brought into action to attain the best accuracy and identification of tumors. ML is significant in accurately predicting the existence of the tumor inside the brain. Due to the affected area of abnormal growth of cells region that leads to glioma in the brain. Mostly 80 percent of brain tumors are affected by glioma and the survival rate is 12-18 months. A risk factor can increase higher chances of developing a brain tumor. Although risk factors may be a great cause for the development of a brain tumor, most people do not cause it directly. Some people with different risk factors never develop a brain tumor throughout their life, while others with no known risk factors may be affected. Knowing the risk factors and discussing them with the doctor may prevent us from making more informed decisions. However, there are no proper causes to prevent a brain tumor at this time through lifestyle changes. When affected, fast and accurate detection is the best choice. Deep learning (DL) is an emerging field and it has gained a lot of popularity in solving many medical applications and treatments. Numerous researchers have utilized DL to find brain tumors using deep learning methods. Higher performances of DL have empowered researchers to identify precisely the exact location of tumors. Recent years have witnessed a new variation of the Deep Transfer Learning approach that takes over the field of image classification, object recognition, and image visual categorization issues [4]. Transfer learning is a strategy for domain adaptation that employs a pre-trained CNN model that has been originally developed from another application of an identical problem [4]. Transfer learning relates to and allows cross-domain learning problems and imitates extracting information from the source domain and transferring those to the target domain. Specificity, sensitivity, accuracy, and F-1 scores are some of the metrics used in this study to evaluate performance. The location of the brain tumor can also be better visualized from brain MRI images using Gradient-weighted Class Activation Mappings (GradCAMs) based visualization tool. The contribution of the work can be summarized as follows:

- A Fine-tuned light weight EfficientNet V2S model having state-of-the-art performance.
- Exhaustive performance comparison on three different datasets with large variants of disease classes for cancerous and healthy brain cell classification.
- Multigrade classification of tumor classes for three datasets have 44 classes, 12 classes, and 4 classes respectively.
- Illustration of the results by explainable model through GradCam Visualisation

The rest of the work is structured as follows: Section 2 describes the related works using deep learning techniques for brain tumor detection. The steps of the proposed methodology are described in section 3. Section 4 overviews the experimental evaluation. Results and discussion are addressed in section 5. Section 6 concludes the paper.

## 2. Literature review

For building automated brain tumor detection systems, several researchers have employed various algorithms using various sophisticated ML and DL techniques, such as Inception V3 net, VGG 16 net and SqueezeNet. These employ extremely precise techniques to identify brain malignancies in MRI scans. Deep learning is a recent development in machine learning (ML), and it produces cutting-edge outcomes in several study areas, including computer vision, drug design, and bioinformatics. Researchers have also proposed a variety of deep learning-based approaches for identifying and categorizing diseases [6]. Multiple processes which include data collection, model construction, training and multiple-class classification of MRI images, must be completed to establish a framework for brain tumor visualization and its categorization. Despite the advancement of deep learning, which is presently leading-edge in several applications, convolutional neural networks have also been studied and have demonstrated a considerable improvement in brain tumor disease classifications for a wide range of different tumors. In this section, some recent works related to our work are discussed in brief. Sajjad et al. [2] have introduced an architecture utilizing input-cascaded CNN for tumor segmentation and optimized

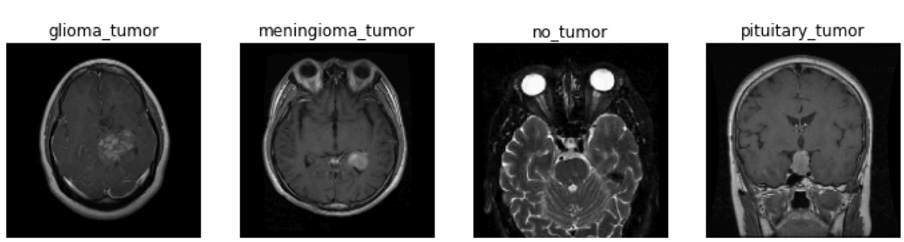


**Fig. 4.** Sample images of of Dataset-1.

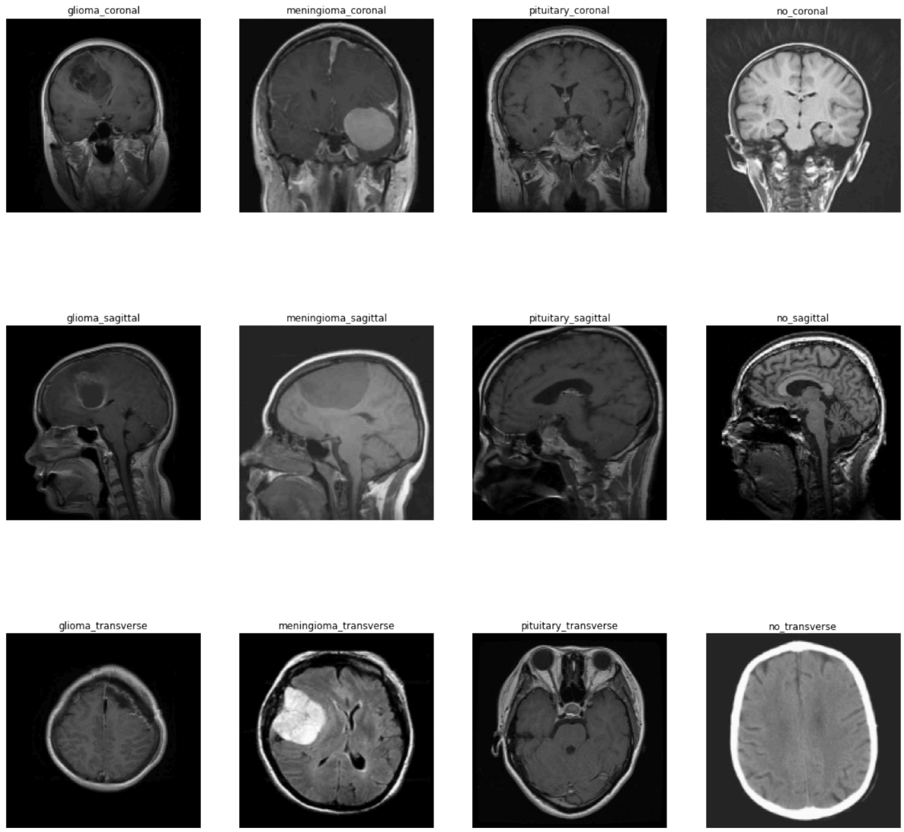


**Fig. 5.** Sample images of Dataset-2.

VGG-19 for three-class tumor classification. Extensive data augmentation is used in their work for better performance and it produced an accuracy of 0.94. Shao et al. [3] utilized the VGG16 transfer learning architecture to recognize brain tumors. SVM-AT and SVM-T are two different versions of the standard SVM method that are evaluated, with SVM-AT learning that is based on samples from both the target and the training set. SVM-T from the target and source domain is learned by employing samples only from the target and source domains and the source domain. Kibriya et al. [4] proposed a CNN-based multiclass brain tumor classification using three grades of tumors. They achieved an accuracy of 96.2% for 3064 brain MR scans from the publicly accessible dataset. Kaur et al. [5] utilized and classified brain tumors using transfer learning and investigated several DCNN models for the categorization of MR brain images. Mittal et al. [6] proposed a modified deep CNN model to classify four classes of tumors and applied the concept of Stationary Wavelet Transform (SWT) and the new Growing Convolution Neural Network (GCNN) which achieved an accuracy of 0.964%. A comparative study with Convolutional neural networks and Support Vector Machines has also been performed in this work. Bahadur et al. [7] applied Support Vector Machines based classifier for the extra niction of relevant features and devised a computer-aided diagnostic system from MR images. Again from the segmented tissues perform the segmentation by Berkeley wavelet transformation (BWT) based tumor segmentation. Rai et al. [8] proposed a hybrid CNN model having a large number of layers and parameters for the automatic detection and accurate segmentation of brain tumors from MRI images. In their work, two models, U-net, ResNet-50, and Vanilla U-net are used for the accurate segmentation of brain tumors. In the paper, Gumai et al. [9], took the most current cutting-edge improvements and the usage of the hybrid feature extraction technique in conjunction with the RELM approach is more powerful.Exactness improved from 91.51 % to 94.233 %. Nahid Ferdous et al. [10] took a unique technique for the exact and computerized classification of brain tumors which employs a two-stage feature ensemble of deep convolutional neural networks (CNN). By optimizing the developed algorithms, the suggested model outperforms other current models, achieving an average accuracy of 99.13%. Deepak et al. [11] extracted attributes from MR pictures, using a pre-trained version of GoogleNet, and attained a mean accuracy of 98%. Selvaraju et al. have classified the extracted features using different classifiers such as softmax, SVM, and the KNN. [12] Over the last few years, multiple researchers have developed a variety of deep learning based disease identification techniques. Using CNN, SVM, and KNN classifiers, the authors were able to attain a mean accuracy of 92.3%, 97.8%, and 98%. Tan et al. [13] thoroughly investigate model scaling and demonstrate that properly balancing network depth, breadth, and resolution can result in improved performance.Pundir et al. [14], employed a pre-trained VGG16 model in their research, and the recommended approach achieved 91.8% accuracy. Polat et al. [15] use transfer learning to detect the most frequent brain tumors using VGG16, VGG19, ResNet50, and DenseNet21 networks respectively, and achieved higher performance in the figshare dataset.This article introduces a unique dense CNN model utilizing pre-trained EfficientNetB0 with dense layers. EfficientNetB0 contains 230 layers and 7 MBConv blocks [16]. It has a large block structure formed up of four densely connected layers with a development rate of 4. Each layer in this structure accepts the output feature maps from the previous layers as input feature maps. The dense block concepts are made up of convolution layers that are the same size as the input feature maps in EfficientNet. Badza et al. [17] introduced a CNN architecture for classifying three types of brain tumors and tested them on T1-weighted contrast-enhanced magnetic resonance images. The pre-trained EfficientNetB7 model was previously trained on a large ImageNet dataset. [18] The pre-trained ResNet18 CNNcould be considered as a modified version of the CNN structure in the proposed model. The recommended model achieves outstanding improvement with the highest-rated accuracy of 98%. Anaraki et al. [19] adopted an ensemble method for the best model provided by the GA. In one case

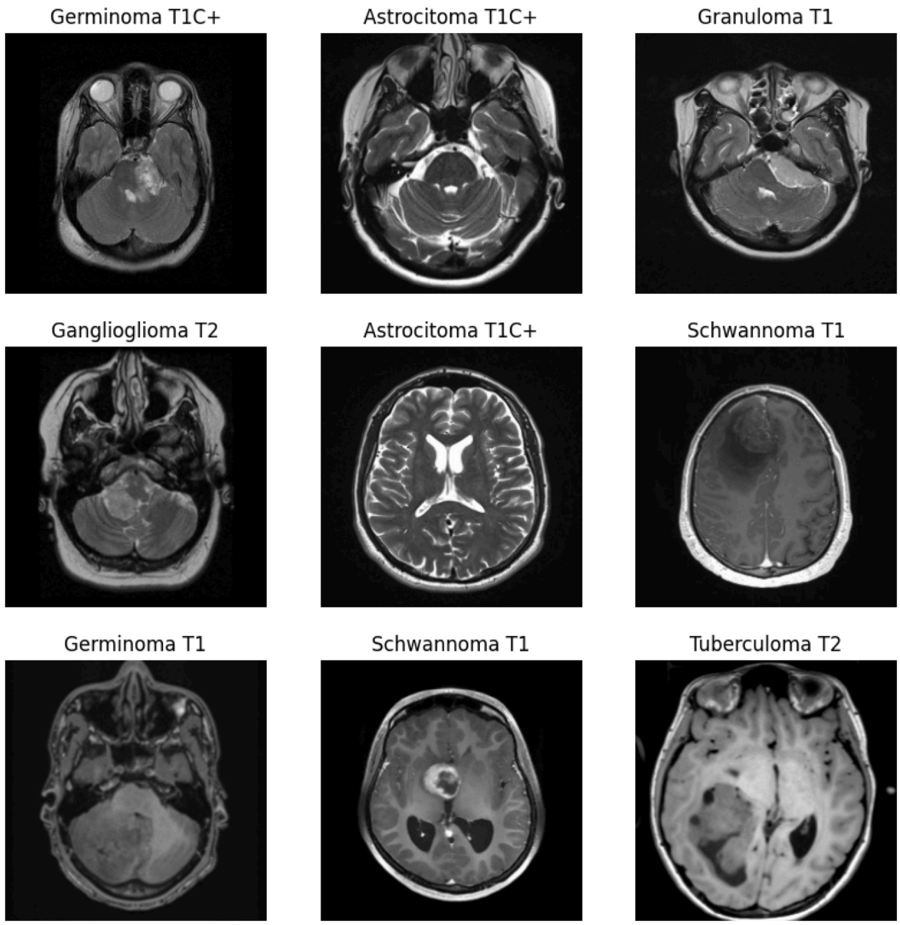


**Fig. 6.** Sample images of Dataset-3.

**Table 4**
Comparision of proposed fine tunned ECNN Model with state of the art methods.

| Author | Model | Datasets | Accuracy | Parameters | Size(MB) | GFLOPS |
|---|---|---|---|---|---|---|
| Sajjad et al. [2] | Input Cascaded CNN, VGG-19 | Radiopaedia 121 MR images,3064 Figshare | 87%,90.67% | 0.43 M | 574 MB | 20.04 |
| Swati et al. [28] | Pre-trained VGG-19 | CE MRI | 94.82% | 61 M | 21.8 | 0.33 |
| Kaur et al. [5] | Inception v3, Resnet101 | Harvard | 98%,94%,95% | 21 M | 23.2 | 45.7 |
| Pundir et al. [14] | VGG16 | Navoneel | 91.8% | 27 M | 106.4 | 7.76 |
| Deepak et al. [21] | GoogleNet | datasets | 97% | 41 M | 160 | 41.2 |
| Our prposed model | Fine-tuned EfficientNet-V2S | 3064 Figshare,erdos 12 classes,fernando2rad datasets | 98.48%,97.9%,95.6% | 20 M | 16.2 | 31 |

**Table 5**
Parameter summary of the Proposed fine-tuned ECNN model.

| Parameters | Values |
|---|---|
| Epochs | 25 |
| Batchsize | 5 |
| Optimizer | Adam |
| Loss function | sparse categorical |
| Learning rate | 1.6e -05 |
| Activation function at input layer | Elu |
| Activation function at output layer | Softmax |

study, this technique produced a 90.9 percent accuracy rate for categorizing three Glioma grade levels. In another case study, tumor types were recognized with 94.2 percent accuracy. On a minimal dataset, the pre-trained model performed excellently. Isunuri et al. [23], developed an effective and associated convolution network for grade classification in brain magnetic resonance images. The feature extraction is done with a pre-trained EfficientNetB0. In their analysis, they employed the REMBRANDT dataset [31] and achieved an accuracy of 96.95%. Sharma et al. [33] used aspects of the ResNet50 model, eliminating the last layer and adding four more levels to accommodate work circumstances. This work employs the upgraded ResNet50 model to provide a novel deep-learning method based on a transfer-learning strategy to classify brain tumors. Dhamija et al. [34] employed the models to capitalize on local and global characteristics by combining transformer-based encoders with convolution-based encoders to segment medical pictures with high accuracy. Both suggested models provide encouraging results, as compared to the state-of-the-art models for multiple segmentation tasks. Sasmitha et al. [25] divided MRI and WSI samples with DenseNet and ResNet, respectively. Tumour-Analyser uses interpretability to give an acceptable remedy to the reduced human understandability of existing models caused by the essential black-box nature of deep learning models and the lack of transparency. Tanvi et al. [27] employed the Discrete Wavelet Transform (DWT) to extract features and Principal Component Analysis (PCA) to select features in their work. Various classifiers such as Support Vector Machine (SVM), k-nearest Neighbour (k-NN), CART (Classification and Regression Tree), and Random Forest are also tested for classification. Zulfiqar et al. [30] applied EfficientNets to conduct a transfer learning-based fine-tuning strategy for the categorization of brain tumors into three categories of tumors, which was extremely successful and yielded encouraging results. The feature was extracted from MRI scans using the EfficientNet-V2S model. It was determined whether the person had a tumor or not using a Global Average pooling with a dense layer added as a contrast to a completely linked layer. The purpose of this research is to present a new method for improving and accurately identifying the stage of a brain tumor from an MRI image, as well as to design a way to analyze CNN data using Grad-Cam's Saliency map visualization. The paper aimed to introduce a novel methodology for developing an improved and efficient brain tumor detection of the stages of brain tumors from MRI images. In this paper, a tumor detection and classification model is proposed to provide a solution for disease prediction and detection of brain tumors. The proposed model is lightweight and gives forecasts that are preferred logically over the current strategies. Motivated by EfficientNet's recent success in multiple challenging work, we deployed this method [2].

## 3. Methodology

In this paper, we outlined a unique deep-learning framework that uses a pre-trained fine-tuned CNN model to divide and categorize tumors in the brain into multiple classes. The suggested system comprises of three major steps such as 1)Preprocessing, 2) Data augmentation 3) Deep feature extraction, and Classification of tumors. followed by visualisation of the tumor using GradCAM visualization. Fig. 1 shows the block diagram of the proposed model.

### 3.1. Image Pre-Processing

The model takes a 160x160x3 input image and runs it through the network to identify the brain tumor classifications contained in it. The pre-processing stage's primary goal is to ensure that the input MRI dataset is interoperable with the pre-trained ECNN model. The pre-processing step involves changing the data type of the images, input data normalization, and resizing. The MRI images have low contrast quality due to low illumination and noise. Due to motion heterogeneity and bias field distortion in MR image artifacts occurs during image acquisition. Hence, it is essential to use data normalization and a function of min-max normalization to transform the low-pixel value images into brighter ones. It is composed of two major parts. To categorize brain tumors using transfer learning and extract deep features for much more accurate classifications, the dataset must first be prepared. The input image is normalized to the limited range of 0 to 1 using Eq(1). Assume "D" as representing the input brain MRI of size (mxn), and the normalized MRI is called "Dnorm."

$$Dnorm = \frac{D - \min(D)}{\max(D) - \min(D)} \tag{1}$$

The pre-processed images are split into two groups: 20% for testing and 80% for training. However, just utilizing pre-processed training sets will not allow the pretrained ECNN model to be trained successfully. The training set has to be improved with the use of several parameters to reduce the overfitting issues. The training set must be expanded using a number of features to prevent overfitting.

### 3.2. Data augmentation

For multiple reasons, data augmentation is essential when classifying multigrade brain tumors using MRI images that includes restricted data accessibility, better generalization, robustness to variability, class distribution balancing, less overfitting, better feature learning, etc. Thus, to overcome data constraints, enhanced model generalization, and to guarantee the stability and efficacy of the classification model, data augmentation must be implemented in the multigrade brain tumor classification using MRI images. Our model training aims to increase the accuracy and enrich our dataset. To increase the amount of the current dataset, a method known as data augmentation involves adding slightly modified values to our current data. The steps of the complete data augmentation process have been shown in algorithm 1. Algorithm 1 outlines the step-by-step procedure for the data augmentation technique utilized by the proposed model.

Fig. 2 illustrates sample images generated after the data augmentation process. Here, image datasets only require minimal preparation to address over-fitting issues.

The images are first downloaded and resized per the suggested model. Then they are processed using six different augmentation techniques: rotation, horizontal flipping, zooming, height shifting, and scaling. Table 1 provides the EfficientnetV2S parameter settings used in data augmentation.

### 3.3. Transfer learning

Transfer learning makes use of the knowledge transfer that deep learning entails to tackle new tasks. There are many benefits associated with this approach, including improved performance and shorter training times. There is a significant research gap in multiclass brain tumor classification, even though a lot of research focuses on the binary classification of tumors (tumorous vs. non-tumorous). Furthermore, the majority of multi-class classification models are trained on small datasets. Because of the quick advancement of computer vision technology, numerous good Convolution Networks have been suggested in the literature for the quick development of DL applications. Many researchers have developed different CNN architectures for a variety of applications. With the most powerful feature extraction method, CNNs would detect a brain tumor more easily and with considerably less computing time than other methods. CNN gives a higher speed and excellent performance in detection and classification as compared to traditional neural networks. [20]Transfer Learning is the process of using previously acquired knowledge to solve a problem on a problem that is currently done, with or without changing the knowledge. [3]We have suggested transfer learning in this study because it can learn new tasks and improve categorization by transferring learned information from pertinent classification datasets. A basic convolution neural network is initially trained using a base dataset. The learned features will form a feature map, which is then arranged to be used once more for being included in a target (MR pictures) model that will be trained on the MR images dataset when we acquire the weights. Transfer learning can improve the efficiency of neural networks while decreasing the training time. We conducted comparison research on computation and parameters. The complete algorithm of the proposed Fine Tuned Efficient net model for Multigrade Brain Tumour Classification has been shown in Algorithm 2. In this work, we used a unique classification head on top of the EfficientNetV2 base model, including Global Average Pooling, Dropout layers and Dense (fully linked) layers for classification.

### 3.4. ECNN

Deep learning is used for image classification activities on larger databases and provides better performance than traditional machine learning methods in terms of higher scalability and more accurate classification. [24]EfficientNet is one of the leading deep learning approaches which performs well on the ImageNet database. EfficientNetV2S, a novel family of convolutional networks with quicker training time and higher parameter efficiency than earlier models, is used in this research. In order to improve the performance, we made some adjustments to the base EfficientNetV2S model. It enables the network to effectively collect hierarchical characteristics in images, making it well-suited for tasks like the classification of images. We implemented differential learning rates in binary classification to shorten learning time and improve CNN learning. The model is scaled down and the depth, width, and resolution of the entire dataset are evenly scaled in this manner to produce the most effective results. EfficientNetV2S combines inverted bottleneck MBConv with squeeze and excitation optimization. The EfficientNetV2S model is designed using seven MBConv blocks in series with each other [23]. MB Conv is the fundamental component used in this model. It is an essential part of the architecture that is used to efficiently model complex patterns in images while keeping the model's computational and memory needs as low as possible. First, visual characteristics are extracted using the convolutional layers of Efficient-Net. In order to increase the activation of significant elements, features are then re-weighted using the attention process. Eight different versions of Efficient-Net are offered. EfficientNetV2S was chosen as our backbone network due to its excellent performance in comparison to other architectures and its lightweight characteristic. Depth wise Separable convolution is used to augment the feature vector produced by the pre-trained EfficientNet, which reduces the computational cost by combining each input channel independently with a unique filter. Weights are randomly initialized to get consistent outcomes while training models. In this work, we employed a new classification head on top of the EfficientNetV2 base model, with Global Average Pooling, Dropout layers and Dense (completely connected) layers for classification. Dropout layers avoid overfitting by randomly setting the percentage of input units to zero throughout training. This model includes early stopping, which monitors the validation loss and terminates training if it does not improve after a certain number of epochs. It also restores the best weights identified throughout the training process. Fig. 3 illustrates the architecture of the proposed fine tunned EfficientNetV2S framework. Table 2 shows the performance of the state-of-the-art methods from the literature that make use of deep learning approaches.

## 4. Experimental assessment

### 4.1. Datasets

Three publicly accessible datasets are used to measure the performance of our proposed fine-tuned ECNN model. The descriptions of all the datasets considered in the experiment are given in Table 3.

#### 4.1.1. Dataset-1

The, dataset-1 is Figshare dataset [32] which is publicly available and shown in Fig. 4. Many researchers utilize this dataset to find tumors which was produced by Nanfang Hospital in China. There are 3064 T1-weighted images in the dataset, divided into four classes.

#### 4.1.2. Dataset-2

The dataset-2 [36] is another publicly available dataset shown in Fig. 5. This dataset consists of over 3200 MRI scans, having twelve categories based on the tumor type (glioma, meningioma, pituitary, or none) and the plane of the anatomical coordinate system on which the MRI image was recorded (coronal, sagittal, or transverse). Numerous imaging planes have been employed to offer an extensive view of the brain from different perspectives. Each plane provides distinctive information about the brain, aiding in the precise location and characterization of brain tumors.

#### 4.1.3. Dataset-3

Dataset-3 [35] is a customized collection of T1, contrast-enhanced T1 and T2 magnetic resonance images of organized brain tumor kinds. The images have been categorized as astrocytoma, carcinoma, ependymoma, ganglioglioma, germinoma, glioblastoma, granuloma, medulloblastoma, meningioma, neurocytoma, oligodendroglioma, papilloma, schwannoma, and tuberculoma which contain 44 classes of mri images. This dataset shown provides the sample images of dataset-3 shown in Fig. 6.

### 4.2. Experimental configuration

This section has explored more of the experimental background details of our research work. All simulations are done using Python software in 8GB RAM and Google Colab GPU service. The key libraries for the implementation of the ECNN and all the comparable models are Keras, and Matplotlib.

#### 4.2.1. Training

With a learning rate of 0.000016 across 25 iterations, the proposed ECNN model is used for identifying and categorizing brain tumors. For all the experiments with different datasets, the model performance is measured using the Adam optimizer and sparse categorical cross-entropy loss function. The Efficient-net data is used by the ECNN to modify the model parameters. The employed early stopping callback is also used which is an excellent way to avoid overfitting. It will monitor the validity loss and terminate training if it begins to rise. It is employed to lower the loss function over less computation time.The sparse categorical cross-entropy loss function is given in (2).

$$x = -\sum_{c=1}^{M} y_{i,c} \log(p_{i,c}) + (1 - y_{i,c}) \log(1 - p_{i,c}) \tag{2}$$

where c denotes the appropriate classification for the observation, y denotes the class name for multiple classes, M is the number of classes and P is for anticipated probability. A classification forecast may be accurate or inaccurate. In classification performance, true positive (TP) is The number of tests that are both true negatives (TN) and expected to be in class B. False-positive (FP) tests are those that belong to class B but were predicted to be in class A, whereas false-negative (FN) tests are those that belong to class A but are expected to be assigned to class B.

Table 4 shows the comparative outcomes of all models used with the same experimental data. Additionally, Table 4 includes a list of each model's overall amount of parameters, the number of Floating-point operations per second(FLOPs), and the total memory size. The results show that the suggested fine tunned ECNN model performs better than other state-of-the-art techniques and produces exceptional outcomes on all datasets.

There are 20 million parameters in the CNN model that [5] presents. In contrast to the 61 million trainable parameters in the model described in [28], the design of the model in [21] contains over 41 million features 21 million of which are trainable. The other 20 million parameters are set as ImageNet [21] parameters. Compared to the three methodologies [5,28], and [21] our approach uses only 20 million parameters. Though having a small memory size and appearing to be well suited for mobile applications, the model in [24] only achieves 87.38% accuracy on the Radiopedia datasets and 90.67% accuracy on the 3064 figshare dataset. MobileNet v2 is the only lightweight model that challenges the ECNN. The suggested model has larger FLOPs than any other lightweight model currently in use. Parameter summary of the proposed fine-tuned ECNN model is presented in Table 5.

## 5. Results and discussion

The suggested methodology evaluates brain tumors in magnetic resonance images, monitoring and diagnosing tumor regions across age groups. This work used three datasets: Figshare images, Erdos visuals of 12 classes, and the Fernando dataset of 44 classes. MRI scans are imported into CNN, and expected outcomes have been verified using the dataset. Based on this, the performance of the CNN model is judged. Images are analyzed, processed, and classified as tumorous or non-tumorous. This section provides the findings achieved after assessing EfficientNets variants that have been fine-tuned for tumor classification. The Dataset-1 includes 4786 images as input, 3998 images for training the model, and 788 images for validation. In the second step, the Erdos 12 classes dataset was tested with Python software, and the findings were verified. Validation results indicate that the proposed ECNN model accurately predicts tumors in magnetic resonance images with an accuracy of 97.5%, indicating good performance. The Fernando 44 classes dataset tested Python software using 4479 images and confirmed the findings. Validation results show that the proposed ECNN model accurately predicts tumors in magnetic resonance images with an accuracy of 97.35%.

### 5.1. Evaluation metrics

Our proposed method has evaluated different performance metrics via Accuracy, Recall, Precision, and F1 score.

#### 5.1.1. Accuracy

Its purpose is to evaluate the overall number of observations with respect to the actual observations.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

A true positive (TP) is the number of samples that have been correctly predicted in a given class A and belong to that class. The number of samples that are both true negatives for class B and anticipated to be class B is called a class true negative (TN). False-negative (FN) observations are samples that belong to class A but are anticipated to belong to class B, whereas false-positive (FP) observations are samples that belong to class B but are anticipated to belong to class A.

#### 5.1.2. Precision

Precision is the proportion of the total number of positive predictions with respect to the total number of positive predictions given by (4)

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

#### 5.1.3. Recall

It is the proportion of total number of positive predictions with respect to the total number of predictions given by (5)

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

#### 5.1.4. F1 score

F1 is the symmetrical center between recall and precision defined by (6)

$$F1score = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{6}$$

The effectiveness of the model is assessed across all the datasets listed in subsection 5.1. The training and validation performance of the ECNN are shown in Fig. 8,9,10 where the plot shows the accuracy and loss after each epoch up to 30 epochs. This section focuses mostly on the results of our proposed work, which produce a classification accuracy between 97% to 98% for all the three datasets. The evaluation metrics derived from the confusion matrix are shown in Tables 6, 7 & 8, and the proposed strategy produced individual classification accuracy values for each tumor type. The model has an average accuracy of 98.37%, 97.4%, and 97.13% for dataset-1, dataset-2 and dataset-3 respectively. The efficiency of the model is further examined using the confusion matrix shown in Fig. 8(b), 9(b), and 10(b) for dataset-1, dataset-2 and dataset-3 respectively. The confusion matrix is generated with the anticipated value on the y-axis and the actual value on the x-axis.

### 5.2. Model's explainability using GradCAM

Class Activation mapping is a better approach for enhancing the model explainability and is used to localize the object parts and to find discriminative features. GradCAM representation produces a heatmap for showing multiple regions of interest using the heat map. To confirm the affected areas of the images and better diagnosis, the model uses intermediate activation maps and GradCAMs. In contrast to ML and CNN's black-box nature, these visualizations carry a special significance. GradCAM decides the distinction between a differentiable result, for example, a class score, and the convolutional highlights in the picked layer.

$$w_k^c = \frac{1}{z}\sum_i\sum_j \frac{\partial y_c}{\partial Aij^k} \tag{7}$$

where $Aij^k$ stands for the activation map of the kth filter in the last convolutional layer. The score for the target class is denoted as $y_c$.The gradient $\frac{\partial y_c}{\partial Aij^k}$ suggests the significance of each activation in the final convolutional layer on the target class score. The heatmap is formed by taking the global average of the gradients defined throughout the backpropagation phase. The gradients are calculated based on the output of the ECNN's final convolutional layer, and they represent how the ECNN's output varies for the input image.

Gradient-weighted Class Activation Map generated by the ECNN is shown in Fig. 7, on certain model images from all datasets. It is observed from Fig. 7, that background regions are neglected in substantial number of cases. Yet, disease area segments in the MRI images are well envisioned in the feature maps. Grad-CAM (Gradient-weighted Class Activation Mapping) is a method for creating heat maps that highlight

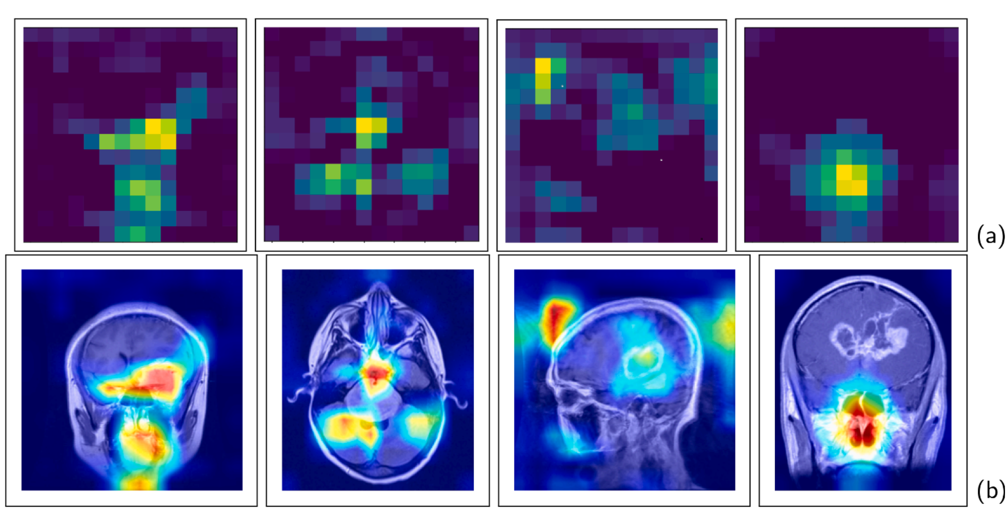


**Fig. 7.** Performance of The suggested fine-tuned EfficientNetV2S (**a**)attention map of brain tumor image sample (**b**)Grad-CAM visualization of MRI image samples.

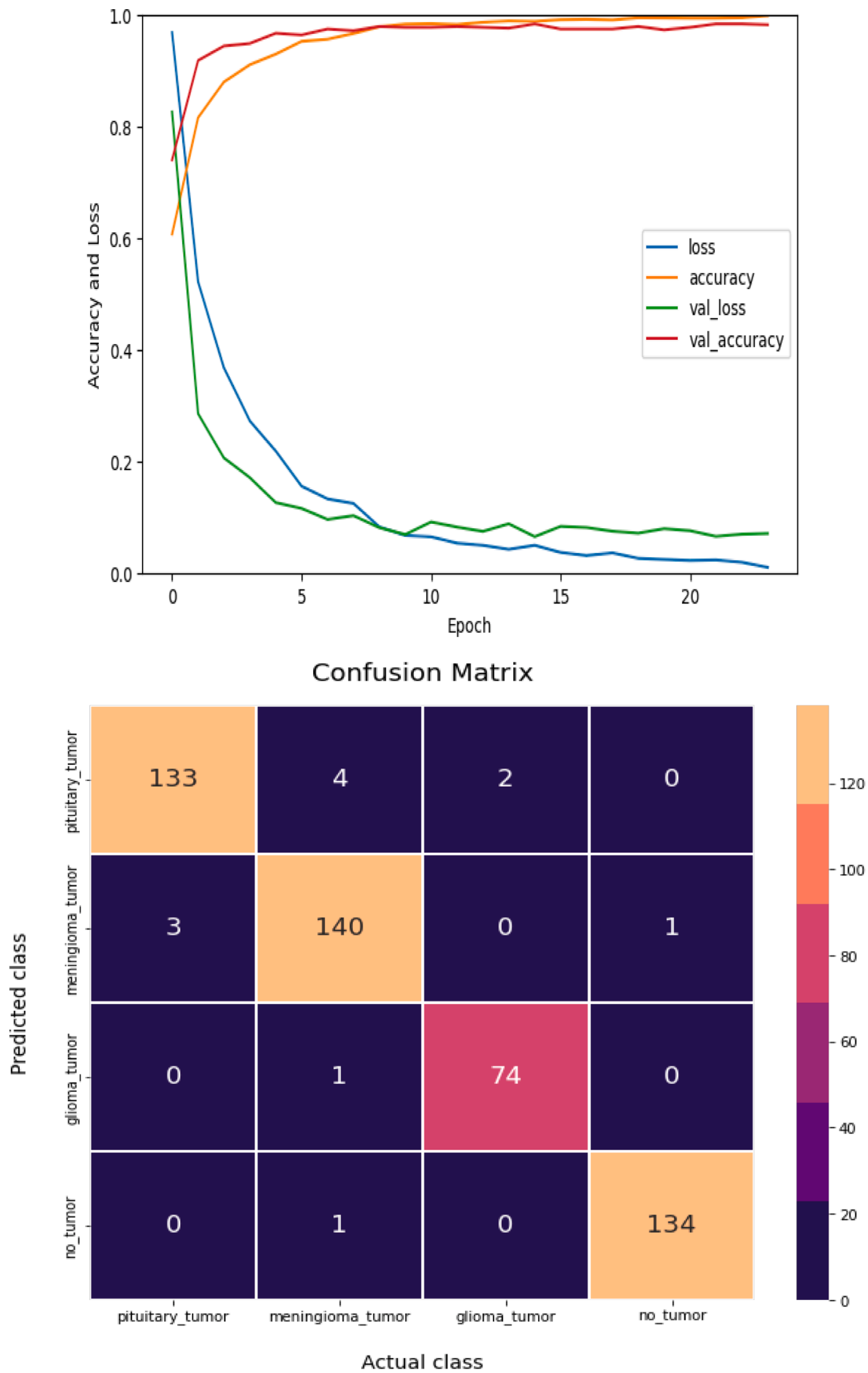


**Fig. 8.** Performance of ECNN on the 4-Class (Figshare) dataset (**a**)Accuracy & Loss for 30 epochs (**b**)Confusion matrix of proposed method for 4 classes of tumor.

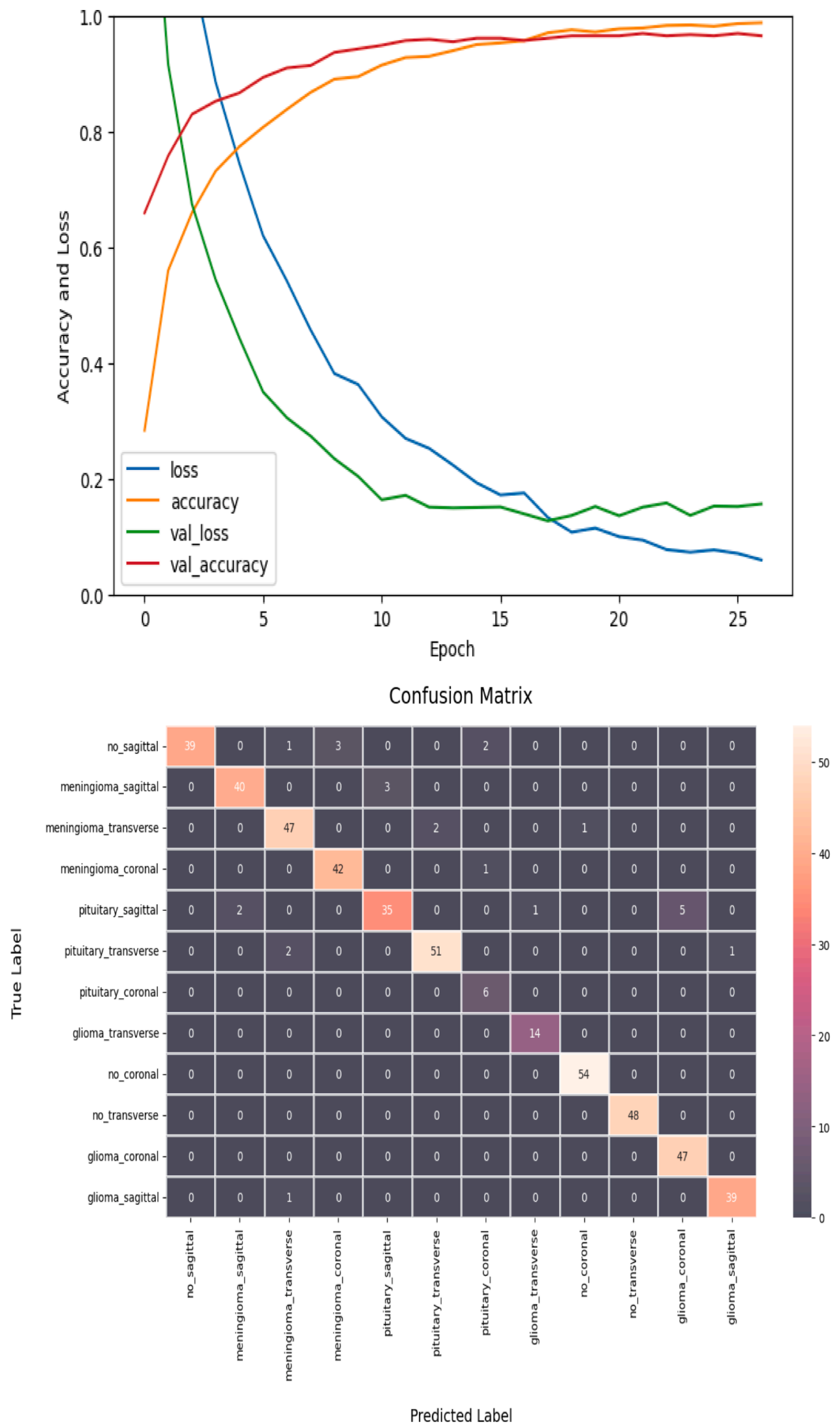


**Fig. 9.** Performance of ECNN on the Dataset 2 (**a**)Accuracy & Loss for 30 epochs (**b**)Confusion matrix of the proposed method for 12 classes of tumor.

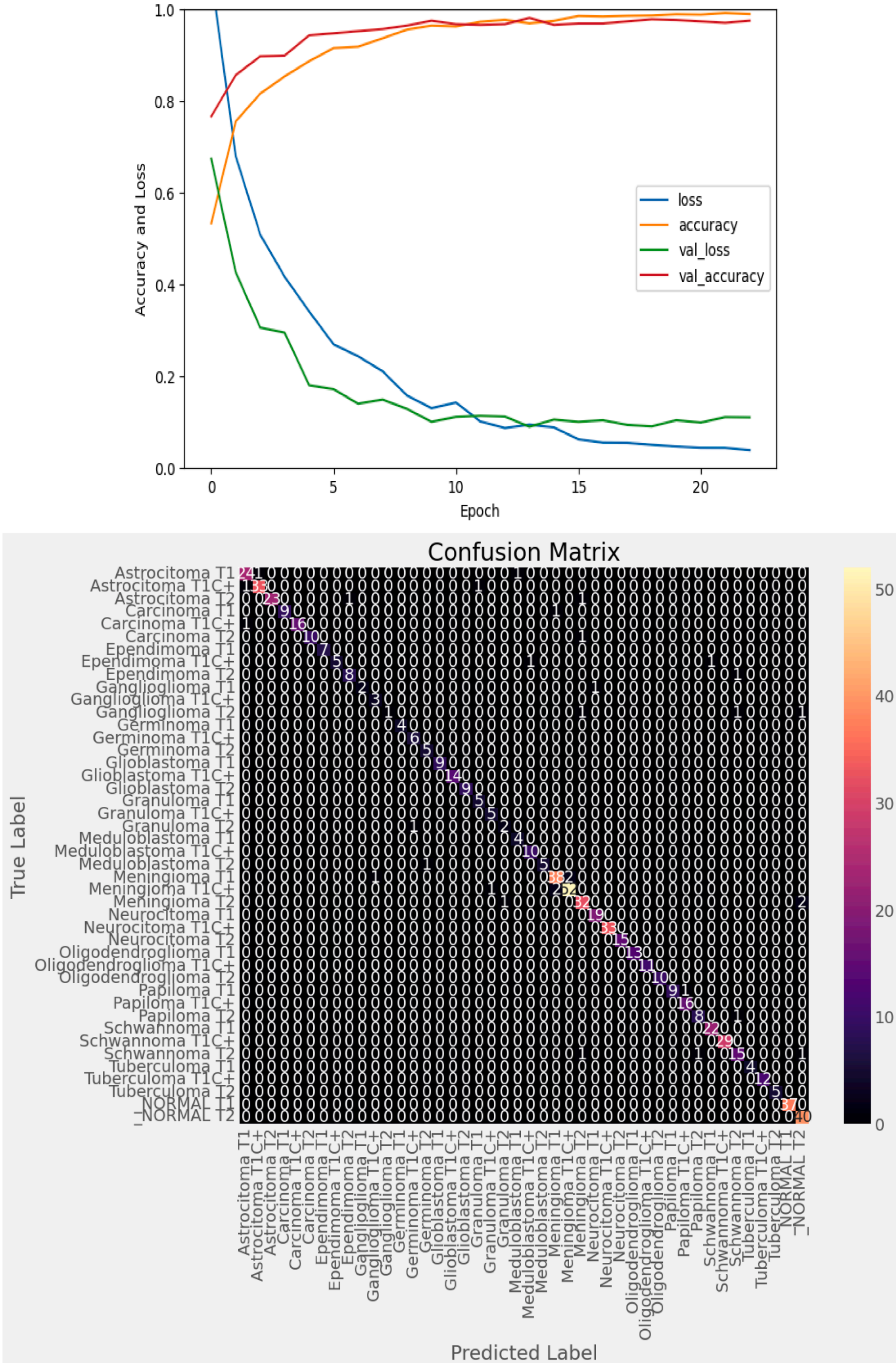


**Fig. 10.** Performance of ECNN on the 44-Class tumor in Dataset-3 dataset (**a**)Accuracy & Loss for 30 epochs (**b**)Confusion matrix of proposed method for 44 classes of tumor.

**Table 6**
Performance analysis for Dataset-1.

| Tumor type | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Glioma | 98.5% | 0.98 | 0.96 | 0.97 |
| Meningioma | 97.45% | 0.96 | 0.97 | 0.97 |
| Pituitary | 98% | 0.99 | 0.96 | 0.97 |
| Nontumor | 99% | 0.99 | 0.99 | 0.99 |
| Avg | 98.48% | 0.98 | 0.985 | 0.9871 |

**Table 7**
Performance analysis for Dataset-2.

| Tumor type | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Glioma coronal | 97.3% | 0.98 | 1.00 | 0.99 |
| Glioma sagittal | 97.8% | 0.93 | 1.00 | 0.96 |
| Glioma transverse | 97.6% | 0.98 | 1.00 | 0.95 |
| Meningioma coronal | 96% | 0.98 | 0.97 | 0.97 |
| Meningioma sagittal | 96.5% | 1.00 | 1.00 | 0.97 |
| Meningioma transverse | 97% | 0.80 | 0.97 | 0.97 |
| Pituitary coronal | 98.4% | 1.00 | 0.97 | 0.94 |
| Pituitary sagittal | 97.4% | 0.97 | 0.96 | 0.97 |
| Pituitary transverse | 96.5% | 0.97 | 1.00 | 0.97 |
| No coronal | 97.4% | 0.91 | 0.97 | 0.94 |
| No sagittal | 96.3% | 0.98 | 0.97 | 0.93 |
| No transverse | 94% | 0.89 | 0.97 | 0.92 |
| Avg | 97.9% | 0.95 | 0.97 | 0.95 |

**Table 8**
Performance analysis for Dataset-3.

| Tumor type | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Astrocitoma T1 | 97.8% | 0.97 | 0.97 | 0.99 |
| Astrocitoma T1C+ | 96.2% | 0.96 | 1.00 | 0.98 |
| Astrocitoma T2 | 96.7% | 0.97 | 1.00 | 0.94 |
| Carcinoma T1 | 98.3% | 1.00 | 0.97 | 0.94 |
| Carcinoma T2 | 97.6% | 1.00 | 0.93 | 0.96 |
| Ependimoma T1 | 96.2% | 0.80 | 1.00 | 0.89 |
| Ependimoma T1C+ | 94.3% | 0.89 | 0.97 | 0.94 |
| Ependimoma T2 | 96.7% | 0.96 | 0.97 | 0.94 |
| Ganglioglioma T1 | 98.2% | 1.00 | 0.97 | 0.96 |
| Ganglioglioma T1C+ | 93.5% | 0.91 | 0.97 | 0.94 |
| Ganglioglioma T2 | 97.5% | 0.98 | 0.93 | 0.96 |
| Germinoma T2 | 94.3% | 0.89 | 1.00 | 0.92 |
| Glioblastoma T1 | 93.2% | 0.89 | 1.00 | 0.92 |
| Glioblastoma T1C+ | 93.2% | 0.89 | 0.97 | 0.92 |
| Germinoma T1C+ | 93.2% | 0.89 | 0.97 | 0.92 |
| Glioblastoma T2 | 93.2% | 0.89 | 0.97 | 0.92 |
| Granuloma T1 | 93.2% | 0.83 | 0.83 | 0.83 |
| Granuloma T1C+ | 93.2% | 1.00 | 0.62 | 0.77 |
| Granuloma T2 | 91.2% | 0.67 | 0.40 | 0.50 |
| Meduloblastoma T1 | 97.3% | 1.00 | 1.00 | 1.00 |
| Meduloblastoma T1C+ | 98.6% | 1.00 | 1.00 | 1.00 |
| Meduloblastoma T2 | 91.2% | 0.69 | 1.00 | 0.82 |
| Meningioma T1 | 93.6% | 0.96 | 0.91 | 0.93 |
| Meningioma T1C+ | 91.2% | 0.96 | 0.98 | 0.97 |
| Meningioma T2 | 91.2% | 0.93 | 0.93 | 0.93 |
| Neurocitoma T1 | 91.2% | 1.00 | 0.97 | 0.98 |
| Neurocitoma T1C+ | 98.13% | 1.00 | 1.00 | 1.00 |
| Neurocitoma T2 | 94.2% | 0.95 | 0.90 | 0.92 |
| Oligodendroglioma T1 | 93.5% | 0.92 | 1.00 | 0.96 |
| Oligodendroglioma T1C+ | 96.3% | 1.00 | 1.00 | 1.00 |
| Oligodendroglioma T2 | 92.2% | 0.88 | 1.00 | 0.93 |
| Papiloma T1 | 91.5% | 0.90 | 0.75 | 0.82 |
| Papiloma T1C+ | 95.4% | 1.00 | 0.95 | 0.97 |
| Papiloma T2 | 91.4% | 0.93 | 0.93 | 0.93 |
| Schwannoma T1 | 92.35% | 0.93 | 1.00 | 0.96 |
| Schwannoma T1C+ | 95.4% | 0.97 | 1.00 | 0.99 |
| Schwannoma T2 | 94.47% | 1.00 | 0.88 | 0.94 |
| Tuberculoma T1 | 91.34% | 0.88 | 1.00 | 0.93 |
| Tuberculoma T1C+ | 96.75% | 1.00 | 1.00 | 1.00 |
| Tuberculoma T2 | 91.4% | 0.67 | 0.80 | 0.73 |
| NORMAL T1 | 98.31% | 1.00 | 1.00 | 1.00 |
| NORMAL T2 | 94.2% | 0.95 | 1.00 | 0.97 |
| Avg | 95.6% | 0.93 | 0.93 | 0.94 |

the image regions most crucial to predicting a deep learning model. GradCAM visualization helps to decide to imagine where the model is concentrating its attention. The intensity maps created by Grad CAM are regularly in red and yellow tones, with red indicating higher significance and yellow indicating lower significance.

Grad-CAMs are used to evaluate the model's predictability by specified requirements. Gradient-weighted Class Activation Mapping (Grad-CAM) is a method used in computer vision to produce visual explanations for deep neural network predictions, notably convolutional neural networks (CNNs) [12]. It aids in determining which portions of an input image had the greatest influence on the model's judgment. This technique uses the gradients flowing back during the back propagation process to highlight the important regions in the image. The attention maps can indicate which parts of the input image the model focused on when making predictions for a particular tumor category. The attention maps provide visual explanations of the model's predictions by highlighting the regions of the input images that were most influential in making the decisions. Table 5,6,7 highlight the proposed fine-tuned EfficientNetV2S's accuracy, F1-score, Recall, sensitivity, and specificity predictions on unseen test data for every class.

Fig. 11 shows the average comparison of average accuracy and loss of proposed ECNN with the existing state-of-the-art Deep learning models. It is observed from Fig. 11 that the proposed method has the lowest testing loss and the highest testing accuracy among all the considered methods.

Fig. 12 shows the result of the final convolutional region of the proposed model through the visualization of Grad-CAM by creating heatmaps. It creates a 3x4 grid of subplots, each of which displays an image with its corresponding Grad-CAM heatmap and the true and predicted class labels. This helps visualize which regions of the images were most important for the model's predictions and can be useful for understanding the model's behavior and potential biases. This study presents a unique method for diagnosing tumorsin the brain. The precision of the proposed model influences its effectiveness. The EfficientNetV2S idea, together with feature extraction and Gradcam visualizationapproaches are employed during the model's development. This approach combines transfer learning and fine-tuning with pretrained datasets from CNN.

## 6. Conclusion

To avoid the serious impact, an automated tumor classification technique for early and accurate diagnosis is proposed in this research. Our outcomes featured the potential for utilizing EfficientNets. To train a model on three separate brain tumor datasets, the characteristics of the modified EfficientNetV2S are explicitly customized. To the greatest of our knowledge, this is the first instance in which a large variant of cancers and healthy brain cells are classified using a transfer learning technique of dense CNN modeling for tumor multigrade classification. Several experiments are performed to compare the strength of other models that were previously trained in the suggested modified Efficient Nets. The model's predictions have been evaluated for interpretability using Grad-CAM. Grad-CAM attention maps generated with the proposed fine-tuned EfficientNetV2S efficiently localize and indicate the brain cell's tumorous region. In this work, The suggested modified pretrained EfficientNetV2S technique achieves an overall test accuracy of 98.35%, 97.5%, and 97.35%, precision of 98%, 95.08%, 97%, recall/sensitivity of 98.0%, 97.0% and 95% and F1-score of 98%, 97% and 96% for dataset 1, dataset 2 and dataset 3 respectively. In comparison to current deep learning algorithms, the suggested method outperforms in terms of accuracy, precision, recall and F1 score. Glioma has been shown to have the lowest detection rate, with an F1-score of 0.98, and pituitary, with the highest, at 0.99. The proposed ECNN outperformed other deep learning techniques in terms of performance and classification accuracy. In the future, as an alternative to use dense CNN-based approaches transformer-based architecture for brain tumor type classification,

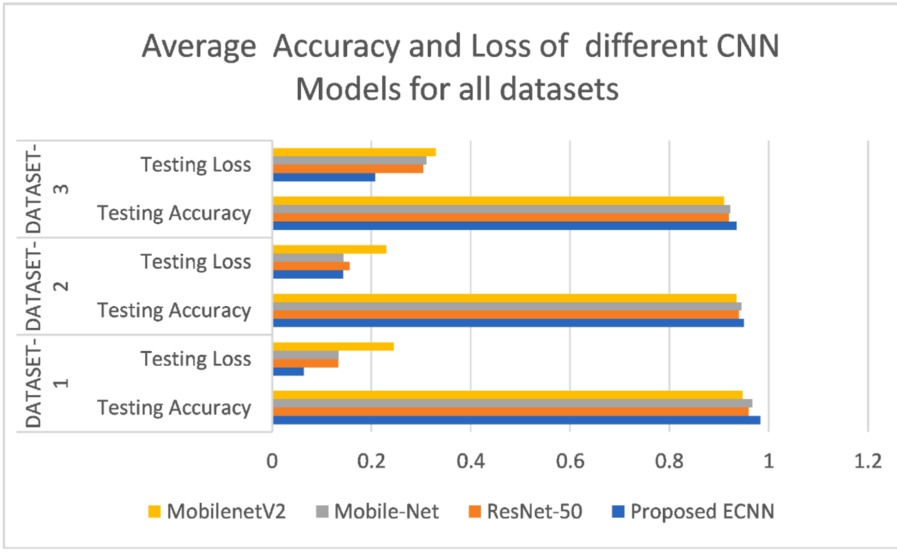


**Fig. 11.** Comparision of Average Accuracy and Loss of Proposed ECNN model with state of the art CNN models.

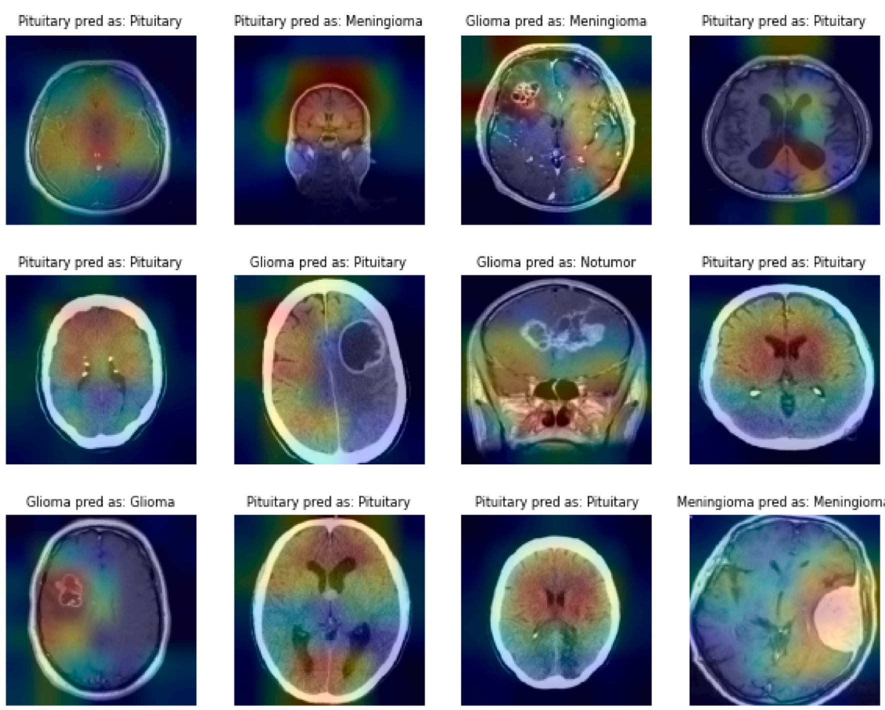


**Fig. 12.** Class Activation maps Visualization of ECNN.

which may extract more information-rich feature maps while reducing network complexity, might be supplied.

## CRediT authorship contribution statement

**Pallavi Priyadarshini:** Software, Writing – original draft, Writing – review & editing. **Priyadarshi Kanungo:** Supervision. **Tejaswini Kar:** Conceptualization, Investigation, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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