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Target Detection and Classification of Brain Cancer Target Detection of Brain Cancer Using CNN

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Abstract:- Brain tumours are regarded as one of the most dangerous diseases in both children and adults. Brain tumours make up 85 to 90% of all primary Central Nervous System tumours. Brain tumours are classified as benign, malignant, pituitary, or other. Magnetic Resonance Imaging is the most effective technique for detecting brain tumours. The use of automated classification techniques such as Machine Learning and Artificial Intelligence has consistently demonstrated greater accuracy than manual classification. The user can use the proposed system as a Web Application. The patient, doctor or medical practitioners, paramedic etcetera are the users for the system. The proposed system acts like an assistant to the doctor, by detecting brain cancer in MRI images. The user will upload the brain MR Image of the patient concerned. Then the system will be able to predict whether the patient has cancer or not, if the patient has cancer the category will be specified. Experimental results indicate that the proposed approach outperforms other commonly used methods and gives an overall high validation accuracy.

Keywords:- *Machine Learning, Artificial Intelligence, Convolutional Neural Network, Transfer Learning, Brain Tumor.*

I. INTRODUCTION

We provide an accurate and automatic categorization approach for three categories of brain tumors in this paper- glioma, meningioma and pituitary tumor. For feature extraction from brain MRI, the solution employs a deep transfer learning CNN model. Known classifiers are used to classify the extracted features. According to the World Health Organization (WHO), the known classifiers of brain tumor are, The grade 1 and grade 2 tumors describe lower-level tumors (e.g., meningioma), while grade 3 and grade 4 tumors consist of more severe ones (e.g., glioma). When tested on the Mohak Keith Nelson (MKN) dataset, the suggested approach has the best classification performance of all the related papers. This paper's significant contributions are given below:

- The notion of deep transfer learning is applied to a 3-class brain tumor classification problem with a validation accuracy of about 84.17%
- When transfer learned deep CNN, features are combined with validated classifier models, performance improves significantly.
- Even with a low number of training examples, the suggested technique achieves a high level of performance this is due to the use of 3264 MRI’s provided with the help of data preprocessing techniques which includes image cropping, image augmentation and pickling applied to the dataset acquired from kaggle.
- We systematically studied model scaling and identified that carefully balancing network depth, width, and resolution has led to better performance. We trained only on augmented data on ResNet50, MobileNetV2, VGG16, VGG19, DenseNet201 and EffNetB0 out of which EffNetB0 had the highest accuracy, hence it outperformed CNN without Transfer Learning Models

II. RELATED WORK

The authors of paper [1] developed an unsupervised machine learning model capable of detecting real-world latent infectious diseases by mining social media data. Before the social media data is preprocessed, an unsupervised sentiment analysis model is presented. Symptom weighting vectors are created for each individual and time period, and latent infectious diseases are retrieved.

The authors of the paper [2] uses data from various health and medical informatics such as Electronic Health Records (EHR) along with data from other sources such as social health, wearable devices. The data is processed using parallel programming paradigms such as MapReduce. Several open-source frameworks such as Hadoop have been considered to store distributed databases as well.

The authors of the paper [3] describe cutting-edge ML methods for anti-cancer drug response modelling and prediction, as well as future opportunities for producing anti-cancer drugs. In this paper, supervised machine learning models are used to predict drug responses using the best-performing approach of Bayesian Efficient Multiple Kernel Learning (BEMKL) combined with the Multiple Kernel Learning (MKL) algorithm.

In paper [4] the authors analyze the DNA sequences of 5 Ebola viruses: Bundibugy ebola virus, Reston ebola virus, Sudan Ebola virus, TaiForest ebola virus, and Zaire ebola virus and investigated the difference between them based on the genus they are involved in, and checked the frequency of the amino acid and found the similarities between the viruses.

In the paper [5,] AI is an attempt at human intelligence that produces intelligent machines that process data. Its main goal is to create brain–like machines. AI has been used in a variety of fields, including robotics, natural language processing, expert systems, image processing, and so on.

Machine Learning serves as the foundation for AI and includes a variety of disciplines such as convex analysis, approximation, probability, and complexity theory. To recognise and identify brain cancer, the authors used a variety of tools such as image segmentation, classification, and tensorflow.

A deep learning-based framework for brain tumour segmentation and survival prediction in glioma using multimodal MRI scans is described in paper [6]. The authors use ensembles of three different 3D CNN architectures for robust tumour segmentation using a majority rule. The training set included images from 285 patients, including 210 HGG (High-Grade Gliomas) and 75 LGG (Low-Grade Gliomas) (Low-Grade Gliomas). The validation set included MRI scans from 66 patients with unknown grade brain tumours that used CNN, 3D U-NET, and other techniques.

It is found that early detection of cancer is the key to lower death rate. In paper [7], overviews of using AI technology for cancer diagnosis of three types of cancer have been demonstrated: breast cancer, lung cancer, and liver cancer. Several studies are reviewed for the various types of systems used for cancer early detection. Automated or computer-aided systems with artificial intelligence (AI) are being considered because they provide a perfect fit for processing a large dataset with accuracy and efficiency in detecting cancer. The detection of tumour metastasis at an early stage is critical for clinical treatment. In the field of medicine, artificial intelligence (AI) has shown great promise. As a result, the authors of paper [8] sought to assess the diagnostic accuracy of AI algorithms in detecting tumour metastasis using medical radiology imaging. AI algorithms may be used to diagnose tumour metastasis using medical radiology imaging with sensitivity and specificity comparable to or even better than health-care professionals. The pooled sensitivity for machine learning was 87 percent (83–90 percent), and the pooled specificity for deep learning was 86 percent (82–89 percent). The pooled specificity for machine learning was 89 percent (82–93 percent), and the pooled sensitivity for deep learning was 87 percent (82–91 percent).

In paper [9] the next generation sequencing (NGS) platforms, addressing it has revolutionized the future of precision oncology. NGS offers several clinical applications that are important for risk prediction, early detection of disease, diagnosis by sequencing and medical imaging, accurate prognosis, biomarker identification and identification of therapeutic targets for novel drug discovery.

Many other scientists are much more confident: Melanoma in the future will be diagnosed by AI, the only question is how soon it will happen. But with all the tremendous efforts of scientists and the investments of huge companies, it should be quite soon. The paper talks about the problems faced in the automation technology in the medical field. AI has the potential, in several ways to become an additional precious tool in the hands of doctors struggling to reduce melanoma mortality. The main obstacles of this goal are the misconceptions about the doctor’s role.[10]

Magnetic Resonance Imaging (MRI) and Computer Tomography (CT) are two commonly used methods for re-sectioning and examining abnormalities in the shape, size, or location of brain tissues, which aids in the detection of tumours. Doctors prefer MRI over CT scan because of the advantages discussed later in the paper. As MRI is non-invasive imaging, the path to sectioning a tumour from MRI images of a brain cerebrum is one of the most profoundly engaged areas in the network of medical science [11].

Developing AI in health through the application of ML is a fertile area of research, but the rapid pace of change, diversity of different techniques and multiplicity of tuning parameters make it difficult to get a clear picture of how accurate these systems might be in clinical practice or how reproducible they are in different clinical contexts. Clinical decision support systems (DSS) are in widespread use in medicine and have had most impact providing guidance on the safe prescription of medicines, guideline adherence, simple risk screening or prognostic scoring. These systems use predefined rules, which have predictable behaviour and are usually shown to reduce clinical errors, although sometimes inadvertently introduce safety issues themselves[12].

In paper [13presents a brain tumour classification system that is accurate and fully automatic, with minimal pre-processing. To extract features from brain MRI images, the proposed system used the concept of deep transfer learning. For improved performance, the features were combined with tried-and-true classifier models. Other metrics were used to evaluate the system's performance in order to determine its robustness.

The following are the limitations of existing works on the classification of brain cancers into meningioma, glioma, and pituitary tumors. The incidence and mortality rate of brain cancer has been reported to be 3.4 and 2.5 respectively per 100,000 people in the world [18] Since privacy of the patients is one of the main concerns, acquiring a large amount of MRI scans is a stumbling block. The accuracy of machine learning models depends critically on the availability of high-quality training data from a large sample size. Image processing, accuracy and identification on a large scale is a complication with regards to processing time. Image segmentation along with CNN classification detects three different types of brain tumors with the accuracy of 61%. We suggest an approach in which a user i.e Doctor/patient can access a transfer learning-based detection and classification system over the internet and be able to get highly accurate results.

III. METHODOLOGY

Transfer learning is a method for gaining knowledge a new set of data from an already trained model. The goal of transfer learning, provided a source domain (Ds) and a learning task (Ts) in the source domain, a target domain (Dt) and the corresponding learning task (Tt), is to improve learning in Dt using knowledge from Ds and Ts [14]. Depending on the type of task and the nature of the data available at the source and destination domains, different parameters for transfer learning are provided. Inductive transfer learning is the transfer learning methodology used when labelled data is available in both the source and target domains for a classification job. In this case, the domain is represented as D = (xi yi) ∀ i, where xi is just the feature vector for the ith training sample and yi is the class label. [15] Figure 1 depicts the transfer learning configuration for our application.

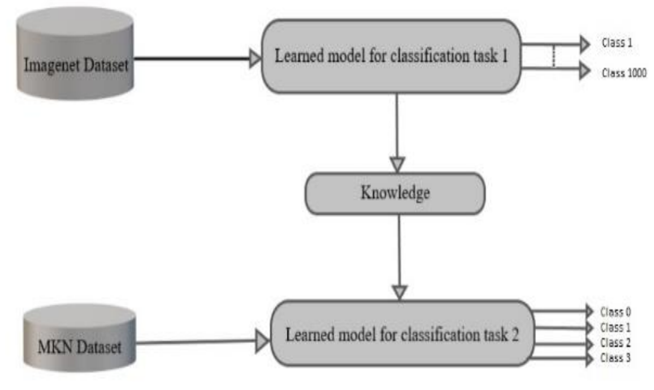

FIG. 1. TRANSFER LEARNING SETTING.

Transfer learning consists of taking features learned on one problem, and leveraging them on a new, similar problem. Transfer learning is usually done for tasks where your dataset has too little data to train a full-scale model from scratch. The above diagram depicts how transfer learning in the form of EffnetB0 is utilized to overcome any barrier brought about by absence of information. We changed the last three layers of EffNetB0 to adjust it to the objective space i.e., cerebrum cancer. The exchange learned and adjusted profound CNN then, at that point, was utilized for tests utilizing MRI information from the MKN (Mohak Keith Nelson) dataset.

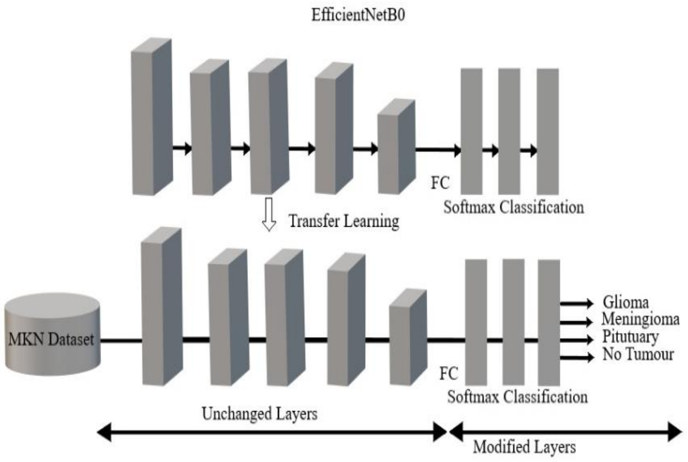

FIG. 2. MODIFYING EFFNETB0 FOR THE APPLICATION.

EfficientNetB0 is a convolutional neural network design and scaling strategy that utilizes a compound coefficient to scale all dept/width/goal aspects equally. The EfficientNetB0 scaling strategy reliably builds network breadth, dept, and goal with a bunch of preset scaling coefficients, dissimilar to standard method, which changes these elements arbitrarily. To utilize 2N times more computational assets, then, at that point, we can basically raise the organization profundity by aN, the width by bN, and the picture size by cN, where a,b,c are steady coefficients acquired by a small matrix search on the underlying minimal model.EfficientNetB0 uses a compound coefficient Φ to uniformly scales network width, depth, and resolution in a principled way.

Convolutional Neural Networks (ConvNets) are commonly developed at a fixed resource budget, and then scaled up for better accuracy if more resources are available. We assessed various different exchange learning calculations regarding our dataset as seen later in table 2. We characterize our undertaking as the characterization of cerebrum cancers into four sorts. T1-contrast upgraded (CE) MRI pictures from MKN dataset structure our dataset and characterize the objective area. The completely associated (FC) layer in the first EffNetB0 was taken out. All things considered, another FC layer with a result size of four was embedded. The softmax layer, following the FC layer, and the cross-entropy-based grouping layer at the result were supplanted with new ones. The altered profound learning model is displayed in Figure 2. Then, at that point, we played out a calibrating of the changed EffNetB0 via preparing it with MRIs. The objective was to prepare the organization to learn dynamic undeniable level area explicit elements. The pre-prepared layers from the first EffnetB0 were expected to become familiar with the significant level attributes. The adjusted model was utilized in preliminaries with MRI.

Figure-3 describes the overall framework for the proposed classification scheme. Deep CNN features from training and testing data, along with class labels from training data, are fed into the classifier model. The model predicts and outputs class labels for the test data.

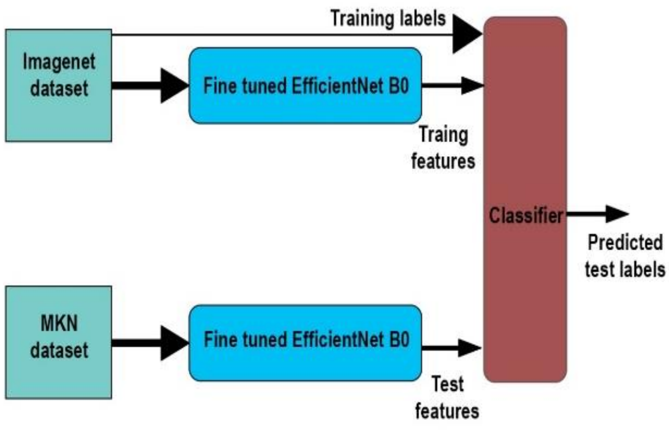

FIG. 3. OVERALL FRAMEWORK FOR BRAIN TUMOR CLASSIFICATION

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IV. EXPERIMENTAL RESULT

The kaggle dataset [17] is freely available and is frequently used to test classification and retrieval methods [16]. The authors in this paper applied data preprocessing techniques as mentioned above in order to enlarge the dataset. Before data pre-processing the dataset contains 253 MRIs that was split into two folders-1. Yes, folder containing images of samples with brain tumor present in it; 2. No folder containing images of samples with brain tumor absent in it. This data is unclean and contains a few images that were incorrectly placed and had to be corrected, deleted, or replaced. A black background surrounds the central image of the brain in the MRIs. The black background contains no information about the tumour and would be useless if fed to neural networks. As a result, cropping the images around the main contour would be beneficial.

Class	Categories of brain tumor	Train	Test	Total
0	Glioma	648	278	926
1	Meningioma	656	281	937
2	No tumor	350	150	500
3	Pituitary	631	270	901
	Total	2285	979	3264

Table 1 Brain tumor image dataset

The amount of data collected was inadequate, which could cause the models to under-fit. As a result, we employed a Data Augmentation technique to increase the amount of data. To create similar images, this technique employs rotations, flips, changes in exposure, and so on. Using this technique, we can greatly increase the size of data. The cropping stage's output image is fed into Image Data Generator, a function in the keras.preprocessing.image library. This function accepts multiple arguments that determine how Augmentation occurs. ImageDataGenerator generates multiple images with the appropriate arguments, which are then saved in a separate folder. The augmentation process is applied to each image in the data-set, causing the data-set to grow in size.

After data preprocessing 3264 brain MRIs were generated. The images are from a T1-CE MRI scan with coronal, sagittal, and axial views. The dataset was segregated into four different classes which are Glioma - Class 0, Meningioma - Class 1, No tumor - Class 2, Pituitary – Class 3 as seen in Table.1. The dataset was first split into 80-20 ratio, however we resorted to 70-30 ratio to optimize accuracy. Given in Table-1 is the tabular representation of the dataset used in this project.

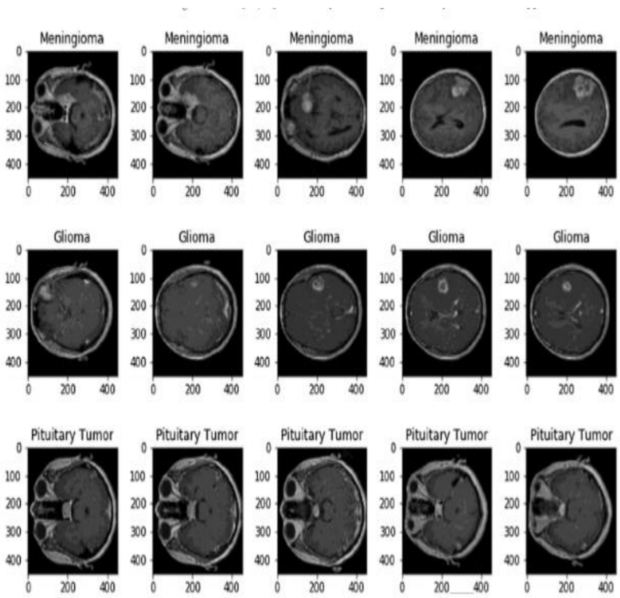

FIG. 4. EXAMPLES OF CLASSES OF MRIS FROM MKN DATASET.

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A. Classifier settings for EffnetB0 Algorithm

The blend of picture features and the classifier model determines how well an image classification system performs. The Adam advancement calculation is a stochastic angle plunge expansion that has been broadly utilized in profound learning applications, for example, PC vision and natural language processing. It was It was the picked as optimizer, considering its great learning rate and the boundary explicit versatile nature of the learning rates. For Adam, the initial learning rate was picked as 0.0001. The decision of a high value of the gaining rate could keep the loss function from joining and could cause overshoots. Additionally; the learning rate has a moderately low value; this extends the training time frame. The size of the mini-batch was set to 32. The option is a compromise between the speed of training and the cost of training. The computational needs (limit) and the size (faster training) is specified by the computer's requirements. The loss function utilized is cross-entropy as it determines the degree to which the projected and actual outcomes are similar distributions. At the modified FC, a faster learning rate is preferred so that the MRIs image's individual features can be learned.

B. Performance metrics and evaluation

For the standard evaluation of a classifier, several performance measures are defined. Classification accuracy is the most widely used quality metric. Accuracy is defined in classification as the number of correctly classified samples divided by the total number of data samples. The following are the categorization accuracies that we acquired in our experiments. The deep transfer learning model has a classification accuracy of 99.4%. When the test dataset contains an equal number of samples from each class, classification accuracy is a useful way to quantify performance. However, the dataset used in the analysis isn't the same as the one used in the previous section. An uneven dataset is a classification problem. This needs a more thorough assessment of the proposed system using additional performance indicators. To investigate the performance of our tumor, we employed confusion matrices.

C. Comparison between algorithms

A Transfer Learning based CNN system for the detection and identification of brain tumors is proposed in this paper. This study makes use of MRI images, which are the most common imaging technique for brain tumor scanning.

Algorithm	**Train Test 70/30**				**Train Test 80/20**				**Epoch**
	Accuracy	**Loss**	**Validation Accuracy**	**Validation Loss**	**Accuracy**	**Loss**	**Validation Accuracy**	**Validation Loss**	
CNN	98.08	0.0525	65.58	3.4736	97.85	2.2495	78.68	2.2495	15
VGG16	90.74	0.8654	75.89	0.8653	91.21	0.2708	67.01	1.3047	15
VGG19	88.93	0.3233	73.03	0.8993	87.67	0.36	61.42	1.4177	15
EffnetB0	99.4	0.0226	84.17	0.6512	99.21	1.0609	78.93	1.0609	15
MobileNetV2	58.73	1.2972	59.45	1.2942	63.99	1.1745	61.67	1.2894	15
Resnet50	63.38	1.2057	80.9	1.2454	63.03	1.232	77.92	1.2681	15
DenseNet201	76.14	1.2865	76.14	1.2865	63.99	1.236	75.63	1.2865	15

Table 2. Comparative study of algorithm for brain tumor detection.

A Convolutional Neural Network (CNN) is a form of Artificial Neural Network (ANN) that is unique. The development of CNN, a Deep learning algorithm, was influenced by ANNs. Deep Learning is a subset of Machine Learning that uses Deep Neural Networks, which are multi-layer neural networks. The CNN is an ANN in which at least one layer performs a convolution operation before passing its output to the next layer. A CNN is made up of Table 2. Comparative study of algorithm for brain tumor detection. three layers: the convolutional layer, the pooling layer, and the output layer. The entire image is scanned by the convolutional sheet. The Pooling layer samples the convolution layer's output, reducing the amount of data that needs to be learned. The convolutional and pooling layers are often used several times. The outputs from previous layers are combined into a single vector that is added to the next layer by the fully connected input layer. To anticipate a value, the fully connected layer creates a weighted sum of the information delivered by the analysis of the features and its examination. To predict, the fully connected layer produces weighted sum of the given input by the function analysis. To foresee a result mark, the fully connected layer delivers a weighted sum of the input created by the component investigation.

The output class is determined by the fully connected layer.

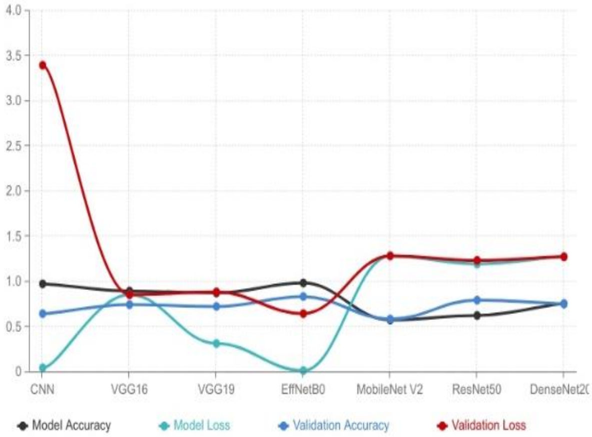

FIG. 5. GRAPHICAL REPRESENTATION OF COMPARATIVE STUDY OF ALGORITHMS FOR BRAIN TUMOR DETECTION FOR DATASET SPLIT INTO 70-30 RATIO

The proposed CNN classifier has five layers: an input layer, a convolutional layer, a max pooling layer, a fully connected layer, and an output layer. The number of neurons in the output layer corresponds to the number of classes.. Given the vast computational resources and time needed to build neural network models on these problems, as well as the huge leaps in ability that they provide a solution on related problems, it is a common approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks. In this paper, we propose that you use transfer learning to accelerate the deep learning model's training and boost its efficiency.

Keras gives you access to a variety of high-performing pre-trained models designed for image recognition. It loads pre-trained weights from ImageNet by default. This model can be developed using either the 'channels first' data format (channels, Table 2. Comparative study of algorithm for brain tumor detection, height, and width) or the 'channels last' data format (channels, height, and width) (height, width, channels). This model's default input size is 224x224.

The EfficientNetB0 scaling approach uniformly scales network distance, depth, and resolution with a collection of defined scaling coefficients, unlike traditional practice, which scales these factors arbitrarily. The validation accuracy for EffNetB0 was the highest as given in Table 2 the value comes out to be 84.17ResNet50 is a ResNet variant with 48 Convolution layers, one MaxPool layer, and one Average Pool layer. It includes 3.8 x 109 floating point operations. It's a well-known ResNet model, and we've gone over the ResNet50 design in depth. The validation accuracy for ResNet50 is 80.9 percent, as shown below.

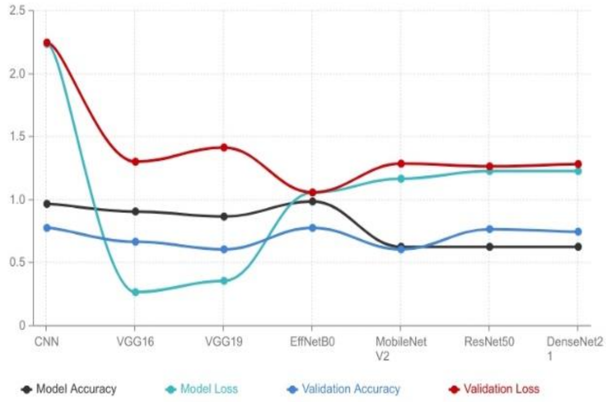

FIG. 6. GRAPHICAL REPRESENTATION OF COMPARATIVE STUDY OF ALGORITHMS FOR BRAIN TUMOR DETECTION FOR DATASET SPLIT INTO 80-20 RATIO

The idea of residual blocks was incorporated into MobileNetV2's depth wise separable convolution layer. The residual network simply adds an identity path around each of the convolutional layers and adds the convolutional block output to the identity path. This enables the network to learn the difference between the identity and allows gradients to propagate more effectively. The validation accuracy for MobileNetV2 as shown below is 59.45%. DenseNet-201 is a convolutional neural network with 201 layers. It is possible to load a pretrained version of the network that has been trained on over a million images from the ImageNet database. The validation accuracy for DenseNet201 is 76.14 percent, as shown below. VGG16 is a convolutional neural network model that, rather than having a large number of hyper-parameters, focuses on having convolution layers of 3x3 filter with stride 1 and always using the same padding and maxpool layer of 2x2 filter with stride 2. This arrangement of convolution and max pool layers is consistent throughout the architecture.. The validation accuracy for VGG16 as shown below is 75.89%. VGG19 is a variant of VGG model which in short consists of 19 layers which consists of 16 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer. The accuracy for VGG16 is 75.89%

V. CONCLUSION

This paper presents a brain tumor categorization method that is both accurate and totally automatic, with minimal pre-processing. To extract features, the suggested system used the notion of deep transfer learning from MRI scans of the brain. The features were combined with a tried-and-true classifier models that will help the model perform better. when compared to all similar works, classification accuracy is the most important factor. Pre-Processing was used to assess the system's performance in order to determine its resilience. Furthermore, the system performed well with a reduced amount of training data. In spite of the way that the achievements introduced in this study, a few upgrades are as yet required which can be, first is the transfer learning model's low presentation as an independent classifier. Second, examples from the class meningioma were strikingly misclassified. Third, with less training data, the issue of overfitting was found. These challenges will be tended to in future space research, perhaps through additional information increase and tuning of the transfer learnt model.

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