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Brain Lesion Detection and Classification

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ABSTRACT
This study proposes an innovative strategy to integrate human brain connect omics with wrapping for brain tumor segmentation and classification. The brain tumors are the worst illness leading to an extremely short lifetime. Brain tumor misinterpretation leads to incorrect medical involvement and a reduction in patient chances of survival. A precise identification of brain tumors is essential for properly arranging treatments for the healing and improvement of the presence of brain tumor patients.
Tomography and Convolution Neural Networks (CNN) were successful and have made key advances for machine learning through computer-aided tumor detection systems. In comparison to the typical neural network layers, the deep convolution layers automatically extract crucial and robust characteristics from input space. To get the ultimate Voxel level classification and segmentation, we employ Deep Neural Network designs, we are doing three investigations in the framework proposed utilizing four neural networks designs such as DenseNet, ResNet and EfficientNet to classify Brain tumor Pituitary, Glioma and Meningioma classes. Each study next analyzes the approaches for the transfer of learning. The data increase method is used for MRI slices in order to generalize the results, to increase samples of the datasets and to reduce the possibility of overlap. EfficientNet was very accurate for classification and measurement up to 97.24% in the planned investigations.
Keywords: Deep Learning, Brain Tumor Classification, RestNet, DenseNet, EfficientNet and Kaggle Datasets (Brain Tumor X-Ray Image).

I. INTRODUCTION

In a number of vision tasks such as classification, segmentation and object identification, Convolutional neural networks (CNN) were quite successful. Fully revolutionary networks [9] do end-to-end semanticization with outstanding outcomes for the first time. In order to increase detail preservation, EfficientNet[13] use a symmetrically designed encoder decoder with skip connections, which is the most important architecture to segment medical picture. In recent decades, illnesses conquered with human ingenuity and biological advancements have stumbled, but cancer remains a plague for civilization because of its unstable nature. Brain tumor malignancy is one of the most dangerous and increasing illnesses. The brain is one of human body's core and most complex organ, including nerve cells and tissue, to manage the body's primary processes such as breathing, muscular movement and sensation. Each cell has its unique functioning, some cells thrive and some lose capacities, resist and are aberrant.

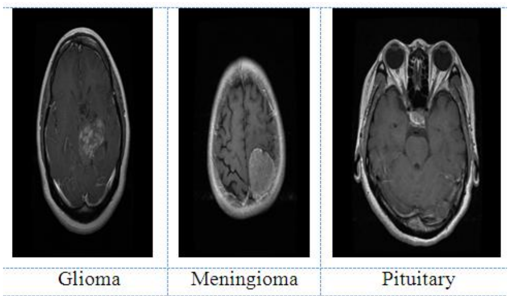

Fig No. 1: Different Types of Brain Tumor

These aberrant cell mass groupings are called the tissue tumor. Uncontrolled and abnormal brain cell growth [12] are cancerous brain tumors. It is one of the worst malignancies to life. Inspired by a natural language processing attention mechanism [1], existing research overcomes this restriction by merging the mechanism of attention to CNN models. Non-local Neural Networks [18] build a plug-and-play non-local operator based on self-attention, capturing the long-distance dependency of the function map, but with high cost of memory and computing. In addition to offering a model for sensitivity and prediction accuracy, **Schlemper** are able to incorporate in typical CNN models with low computational overhead. Transformer [17], on the other hand, is designed for the modeling of longrange dependence in sequence-to-sequence activities and for the sequence of arbitrary places. This architecture is exclusively self-attention based on its whole exemption from convolutions. Unlike earlier CNN-based approaches, Transformer is not only strong in modeling global contexts, but in large scale pre-training processes it can also deliver good outcomes for downstream tasks.

Two forms of brain tumor, benign and malignant, may generally be classified. The benign tumor has been created in the brain and is a noncancerous form (non-progressive), which develops slowly. This form of tumor is thus not believed to be less aggressive elsewhere else in the body. Abnormal cell growth might push the brain tissue or section that can be temporarily removed. In contrast, malignant tumors are cancerous, quickly create with unclear limits, infiltrate other healthy cells and migrate elsewhere in the body. This tumor, when first generated in the brain, is known as the primary malignant tumor. It is called a secondary malignant tumor, if it is produced and propagated to the brain elsewhere in the body [2]. But meningioma, glioma and hypophysis are additional common kinds of brain tumor. Meningiomas are the most common good tumors in the thin membranes around the brain and backbone. Glioma is a kind of brain-shaped tumor [1]. One of the aggressive brain cancers with a minimum survival of close to two years is high quality Gliomas. The development of hypophysis tumors in the brain cells is erratic. hypo physical tumors grow in the brain's hypophysis. These tumors are intrinsically consistent in shape and can develop in any part of the brain. These brain tumor forms are shown in Fig. 1.

Our planned studies are primarily concerned with:

- An inovative and resilient methodology for the transfer and deep learning of brain tumors, which is successful in extracting significant and rich features from a Brain MRI Images dataset, is described.
- In order to examine the three distinct designs of deep networks such as DenseNet, EfficientNet and ResNet, MRI brain tumor pictures are taken and transfer learning techniques are used in the target data set.
- To provide a thorough review of the key elements that influence pretrained model fine-tuning.
- Comparative investigation to detect and classify brain tumors in the accuracy of each architecture of CNN.

II. RELATED WORK

In recent years, a number of researchers have suggested a variety of strategies for identifying brain tumor using MRI imaging. These approaches differ from traditional algorithms to profound learning models. Having the brain tumor detection data – Brain MRI Images [4], we offer the study associated here. **Ali Pashaei [1]** has done a brain tumor classification and via CNN and extreme learning machine (ELM) in 2018 and achieved accuracy of 91% using ELM Technique. **Cheng et al. [**6] have done a brain tumor data set experiment in this area – Brain MRI Images. The tumor region is employed as a region of interest and these regions are broken down into sub regions via the approach of adaptive spatial division. They collected histogram intensity, matrix co-occurrence gray-level (GLCM), and model-based characteristics from Bag of Word (BoW). They showed the greatest accuracy of 87.54%, 89.72% and 91.28% on ring form partition technique derived features. In [5] a further addition was provided by the same authors. For adding local characteristics from each sub-region, they used Fisher Vector. Mean 94.68% average accuracy (map) has been found. Likewise, with the use of Two Dimension Disconcerted Wavelet Transformation (DWT) and Gabor filters approaches, **Ismael and Abdel-Qader** [8] retrieved statistic characteristics from MRI slices. They have categorized the brain tumors with a multilayer sensory network back propagation and found 91.9 percent greatest precision. The Probabilistic Neural Network (PNN) used in **Abir et al.** [1] for brain tumor categorization. The filtering, sharpening, dimensioning and contrast improvement of the GLCM features was conducted and extracted. They achieved 83.33 percent greatest precision.

Although there is yet no enough efficiency with the automated tumor detection systems available, a strong automated computer-based diagnostics systems are required for the identification of brain tumors. Conventional learning machines requires specialized skill and experience. These processes need efforts to segment and manually extract structural or statistical characteristics which may lead to degraded system performance accuracy and efficiency [15]. The profound transfer-based learning algorithms automatically resolve these problems by removing visual and discriminatory characteristics from various convolutionary levels.

These retrieved characteristics should be abundant and strong for categorization. The GLCM was calculated by **Widhiarso et** and the neural network was fed. They stated that GLCM in combination with contrast enhanced accuracy by 20 percent. With this scenario they attained the maximum precision of 82 percent. The work of Brain MRI Images dataset is described in Table 1. **Abiwinanda et al.**[2] had five different CNN architectures and reported the greatest architectural accuracy . The two convolutionary layers, ReLU layer and maximum pool, are included in structure 2 followed by 64 hidden neurons.

References	Features	Model	Accuracy (%)
Cheng et al. [6]	Bag of Words Intensity Histogram	Support Vector Machine	91.28 87.54
Ismael and Qader [8]	Fabor features	Message Passing Neural Network	98.90
Abir et al. [1]	GLCN	Passing Neural Network	83.33
Widhiarso et al. [19]	GLCN	Convolutional Neural Network	82.00
Abiwinanda et al. [2]	Base Model	Convolutional Neural Network	84.19
Afshar et al. [3]	Base Model	CapsNet	86.56

TABLE 1. RELATED WORK OF BRAIN

TUMOR DETECTION AND CLASSIFICATION

They received 98.51% and 84.19% percent respectively in terms of training and validation. Afshar et al. [3] have suggested a novel network for brain tumor classification (CapsNets). The function mappings of the convolutive layer of CapsNet have been updated to improve accuracy. Using 64 feature maps and one CapsNet layer, 86.56% were attained. Table 1 offers an overview of state-of-the-art brain tumor diagnosis and classification strategy for various scientists using traditional manual network functions and model-based deep neural network properties.

III. DATASETS

In order to train and evaluate our model we utilize brain tumor dataset Brain MRI Images from Kaggle, comprised of 3064 MRI brain slices containing 822 meningioma tumour slices, 826 for glioma tumour, 827 for pituitary tumour and 395 no tumour slices.

IV. METHODOLOGY

CNN – BASED ARCHITECTURE

The acronym for a neural network is a CNN or ConvNet. It has been created automatically with fewer pre-processing efforts to recognize essential visual patterns from raw pixels. The 2012 ImageNet Large-Scale Visual Recognition Challenge competition (ILSVRC) delivered a breakthrough and new designs for profound CNNs introduced by raising the complexity and number of coordinated layers of spectacular data set accuracy [7]. In the last few years, the various designs of CNN combined with transferring learning approaches, including fine tuning and freezing, have achieved tremendous success with their increased image classification performance.
We use three common, very advanced architectures in CNN – Brain MRI Images to categorize and diagnose the brain tumor.

EFFICIENTNET B0

In 2012, **Alex Krizhevski** suggested EfficientNet [9]. The ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) data set was successfully trained [20], which comprises 1.2 million photos from 1,000 distinct categories of natural materials. He was the 2012 ILSVRC champion. It consists of 60 million parameters, 650,000 neurons, and 630 million connectors with five layers of convolution, three levels of max-pooling, and three fully-connected layers, the input layer is 227X227 Input layer.

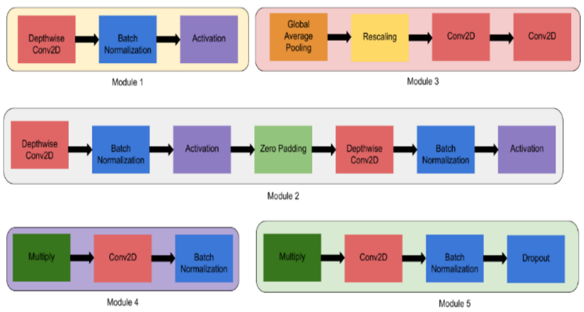

FIG NO. 2: EFFICIENTNET B0 ARCHITECTURE

On input pictures at step 4 in Conv1 the first convolutionary layer applies 96 filters of 11x11 whereas 3 x 3 filters are applied at step 2 in pool 1. Similarly, 256 filters from 5 to 5 are used for the second convolutionary layer. The third, fourth and fifth filter sizes of 3/3 with filters of 384, 384 and 256 are utilized in the same fashion. In each convolution layer the activation function ReLU is used. The layers of fc6 and fc7 are fully linked, with 4096 neurons apiece. In addition, output layer fc8 is used to activate softmax classifier 1000 neurons by ImageNet class.

DENSENET121

In 2014, **Szegedy et al.** created DenseNet [25]. He is the first ILSVRC 2014 champion to get ILSVRC dataset training. Approximately the architecture is as follows

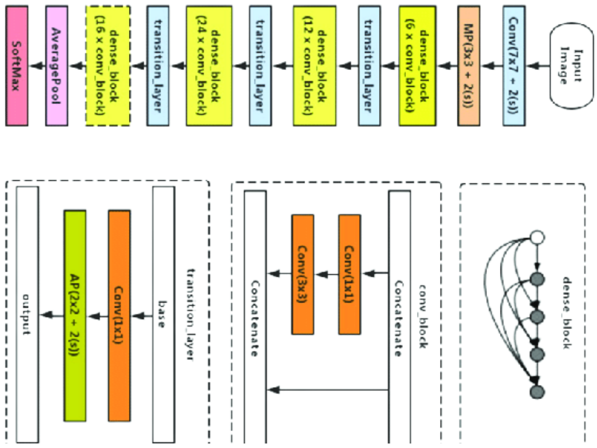

Fig No. 3: DenseNet121 Architecture

6.8 million Settings containing 9 starting modules, two convolutionary layers, four max pool layers, one convolutionary dimensional reduction layer, one average pooling layer, two standardization layers, one fully connected layer and ultimately, a softmax-activated linear layer in the output. Each initial module also includes a single max-pooling layer and six convolutional layers, which are utilized to reduce size by four convolutionary layers. In all fully connected layers is applied the Relu activation function and regularization of dropout is implemented in the fully connected layers. In addition, the original ILSVRC dataset is more accurate than EfficientNet.

ResNet

ResNet, was introduced by Microsoft Research in 2015 calling it Residual Network.

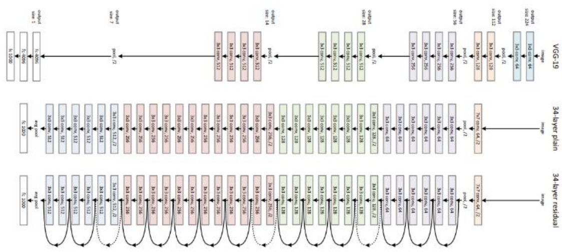

Fig No 4: ResNet Architecture

Confusion Matrices

Calculation measures based on four primary outcomes used for the classification test evaluate the effectiveness of the proposed brain cancer classification and detection systems: true positives (tp), false positive ones (fp), true negative ones (tn) and false negative ones (fn). The suggested system performance must thus be estimated.

Accuracy defines how well the brain tumor kinds can be properly distinguished. To assess a test's accuracy, in all examined cases determined using the following relationships, we determine the fraction of true positive and true negative:

$$Accuracy = {}^{tp+fn}/_{tp+tn+fp+fn}$$

Sensitivity assesses the system's capacity to classify brain tumors properly and is computed by relation utilizing the percent of true positive:

$$Sensitivity = {}^{tp}/_{tp+fn}$$

Specificity is the model's ability to precisely categorize and calculate the real brain tumor type:

$$\text{Specificity} = {}^{tn}/_{tn+fn}$$

Precision is the genuine positive measure and the connection is calculated:

$$\text{Precision} = {}^{tp}/_{tp+fp}$$

V. EXPERIMENTAL SETTINGS

We present the thorough assessment methodologies for the automatic brain tumor categorization and detection system presented in this part. We classify the brain tumor dataset publicly available in Kaggle website. The project uses three CNN models, i.e., EfficientNet, ResNet and DenseNet, prequalified designs. The proposed system includes three primary phases: pre-processing, extraction of features and classification, as shown in Fig. 5.

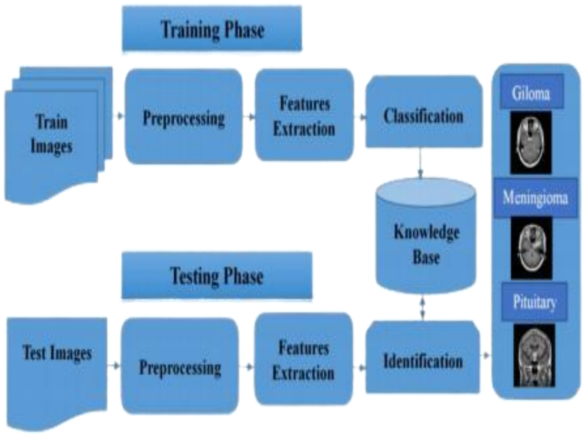

FIG NO. 5: PROPOSED DIAGRAM FOR BRAIN TUMOR CLASSIFICATION

In the first step, the contrast-stretching method enhances MRI pictures. Techniques for data increments like as rotation and rotating are used for massive data generation and over-fitting of CNN architectures. In the following stage, three previously trained CNN architectures in the ImageNet Dataset [6] are used to extract visual and unique characteristics from MRI images in a target brain tumor dataset — Brain MRI Images. During this step each CNN architecture employs transfer learning procedures (EfficientNet, DenseNet, or ResNet). In the last stage automated characteristics are categorized in linear classification.

VI. DATA AUGMENTATION & PREPROCESSING

Preprocessing is the data cleaning procedure that improves and enriches data input for other operations.

To expand the samples of data sets, multiple picture variants are produced utilizing classic data increase approaches that aid to reduce overfitting in CNNs training. We have used a number of strategies of data enhancement (rotation and flip) to enlarge the training data set to provide vast CNN input space. Rotation in which inputs are rotated from a number of angles such as angles 90, 180 and 270 is one of the fundamental ways of data increase. Another option is to flip in the vertical and horizontal direction of the picture. The resulting data increase pictures are shown in Figure 6.

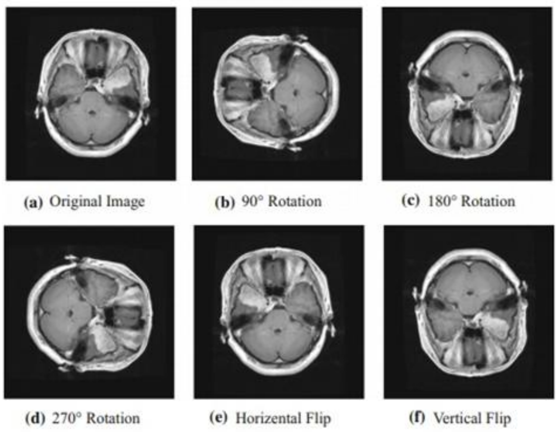

Fig No. 6: Data Augmentation applied on the meningioma image

VII. CNN BASED FEATURE EXTRACTION

After data increase, vast picture samples are produced for the training set, which are the next stage to extract the discriminatory and visual qualities. The effectiveness of deep neural networks is very apparent with the extensive distribution of ConvNets in diverse characteristic extraction strategies [19]. The transfer learning technique, where less dataset samples are available, is one of the important breakthroughs of CNNs. In this work, three pre-trained architectures have been used for extracting features: EfficientNet, DenseNet and ResNet.

VIII. CLASSIFICATION AND DETECTION OF BRAIN TUMOR

By employing transfer learning approaches to successfully extract relevant and crucial visual characteristics and patterns, we are then classifying and detecting the target data set.

IX. COMPARATIVE ANALYSIS, RESULT AND DISCUSSION

The system is experimentally studied using the free publicly accessible brain tumor dataset Brain MRI Images from Kaggle, comprised of 3064 MRI brain slices containing 822 meningioma tumor slices, 826 for glioma tumor, 827 for pituitary tumor and 395 no tumor slices. In training, we used 81% of the data, 9% to confirm and 10% to test. The effectiveness and performance of three designs called EfficientNet B0, DenseNet121, and Resnet are evaluated.

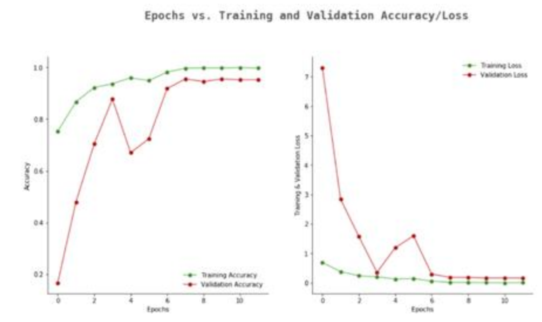

Fig No.7: Experiment Result of EfficientNetB0

EfficientNet B0 is being used in the first research to evaluate the approaches of transfer training.We trained the network with three fundamental solver Adam. The best results are provided with 97.24% accuracy using EfficientNet B0.

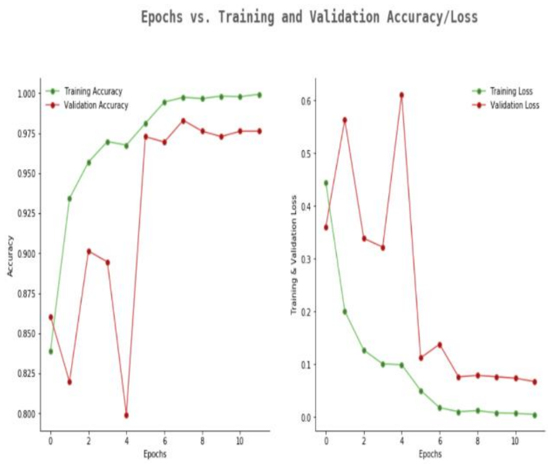

FIG NO.8: EXPERIMENT RESULT OF DENSENET121

In the second research, the model DenseNet121 is used to explore strategies for transfer learning.With the start of 4d-output layer, we have achieved 95.71% precision.

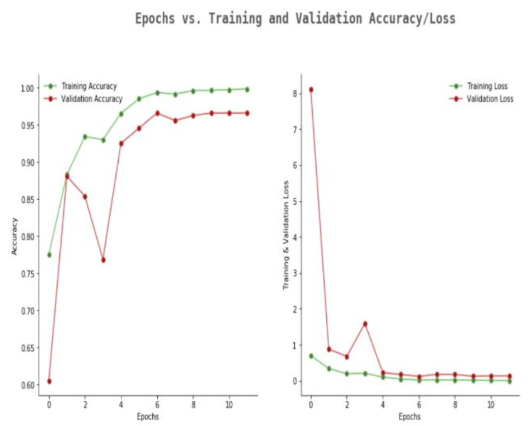

FIG NO.9: Experimental Result of Resnet

The third research examines the efficiency of the transfer learning strategies as indicated in Figure 2, with CNN's Resnet architecture. With Resnet we achieved the highest network accuracy of 95.71%.

We have applied numerous data growth strategies (rotation, and rotation) using raw photos to expand the quantity of training datasets. The EfficientNetB0 achieved testing accuracy of 97.24% as compared to other DenseNet121 and Resnet models.

Table 2 Comparison of Models

Parameter	**DenseNet121**	**EfficientNetB0**	**Resnet**
No of Epochs	12	12	12
Batch Size	32	32	32
Optimizer	Adam	Adam	Adam
Validation Accuracy	95.71%.	**97.24 %**	95.71 %.

We presented a pioneering work for the classification of brain cancers utilizing brain tumor data and obtained maximum accuracy using EfficientNetB0 method up to 97.24% for the publicly available brain tumor data set on Kaggle site,

X. CONCLUSION

The work presented is, in short, a pioneer in the field of the classification of brain tumors employing transfer learning and profound CNN architectures. We have utilized transfer learning techniques employing ImageNet's (source task) natural pictures and categorized the brain tumor kind with the Brain MRI Images dataset (target task). On Brain MRI Images MRI sections for the identification of the tumor kind, we employed three strong deep CNN (EfficientNet B0, DenseNet121, and ReseNet) architectures. Transfer learning is performed to assess and investigate deep-networking performance in order to draw the discriminatory visual characteristics and patterns from MRI divisions. With EfficientNetB0 amongst all trials we get the highest accuracy of 97.24%.

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