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Deep Neural Network-Based Brain Tumor Detection Utilizing CT-Scan Images

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***Abstract:** Brain tumors more typically affect young people and the elderly. It is an aggressive kind of cancer that develops inside the skull as a result of unregulated brain cell development. Tumor cells are notoriously challenging to classify due to their diversity. Promoting clinical diagnostic technology is challenging, though. As a result, medical demands lead to research on computer-aided diagnostics and medical imaging technologies. Convolutional neural networks are getting more and more advantageous for tumor diagnosis. The company has focused more on computer-assisted diagnostic research that uses images of tumors from medical data. The use of neural networks has been widely investigated in the creation of intelligent methods to assist with medical image recognition. . In this paper, the traditional methods of computer-aided tumor diagnosis are discussed. It provides the segmentation and classification of tumor images as well as the diagnosis approaches based on CNN to help physicians recognize cancers. It acts as a manual for future CNN computer-aided tumor detection system development. The resulting network is an EfficientNet adaption with drop-out and thick layers. W have combined data augmentation with min-max normalization to enhance tumor cells' contrast. The advantage of the dense CNN model is that it can accurately categorize a tiny database of pictures. Thus, the suggested strategy provides outstanding overall performance. The experimental results showed that the proposed model was 99.97% accurate during training and 98.78% accurate during testing.*
***Keywords:** Brain tumour, Efficient Net, CNN, Detection*

I. INTRODUCTION

Issues with people's dietary and living environment, such as chemical pollution in the workplace and weakened immunity brought on by a poor diet, may contribute to many tumor problems. Numerous tumor problems, including lung, liver, breast, and a number of brain tumors, have a detrimental effect on people's health and endanger their lives. The word "tumor" [1] describes the newly formed organisms that form a lumpy protuberance that occupies space as a result of local tissue cell proliferation triggered by various tumorigenic stimuli [2]. Depending on its pathological appearance [3, growth method, cellular properties of new organisms, and degree of physical harm, a tumor can be classified as benign or malignant. Cancer and sarcoma are two types of malignant tumors. Clinical symptoms that form from epithelial tissue or hypodermis, alternately, are known by the labels cancer and sarcoma. Malignant tumors (often known as cancer), cardio and cardiovascular diseases, and crashes are the three major causes of death worldwide. The World Health Organization reports that each year there are more than 3.7 million new instances of sickness and more than 1.9 million fatalities [4]. 8.2 million cancer-related deaths are anticipated worldwide in 2012, with binge drinking and smoking accounting for 40% of those fatalities [5]. Despite some preventative efforts, Europe, which has barely one eighth of the world's population and accounts for 20% of mortality, sees about 3.7 million new cases of cancer every year. By minimizing exposure to common risk factors like cigarette smoking, many cancers can be easily prevented. Additionally, the majority of cancers may be cured with surgery, radiation therapy, or chemotherapy. Therefore, it is essential for the successful decrease of cancer death rates during cancer therapy to identify harmful traits early.

Benign tumors in humans are often caused by organ function, local pressure, and congestion. Many times, benign tumors that develop slowly don't endanger the patient's life. However, when the tumor grows, the surrounding tissue compression becomes a symptom.

A. Methods of Tumor Diagnosis

Early stages of cancer do not show any observable signs. Different tumor kinds can occasionally co-occur with certain symptoms. Early recognition of the warning signs can aid in the early discovery of a malignant tumor. A comprehensive examination may be performed if a tumor is suspected in order to provide a full and objective study of the tumor's state, begin treatment straight soon, and increase the cure rate.

Regular laboratory analyses of the patient's secretions and serum, immunological, and genetic testing are examples of traditional diagnostic techniques. X-rays, computerized tomography (CT), magnetic resonance imaging (MRI), ultrasound, single-photon emission computed tomography (SPECT) scan, and others are currently frequently used clinical imaging examinations. Each approach has benefits. Space-occupying lesions of the head can be treated using CT. However, due to bone interference, the CT imaging effect is inferior to MRI when scanning the skull and other brain structures adjacent to the bone wall. nonetheless, is less hazardous and less expensive for the initial diagnosis. If there is a malignancy in the organs, the SPECT examination can visibly depict the form of the organs. Currently, it is frequently used to assess the effectiveness of bone tumor and bone metastasis diagnosis. MRI is clearly superior to CT in the diagnosis of brain tumors, bone tumors, and other types of tumors. However, MRI exams are quite expensive, and patients often report having a negative experience. As a result, CT scans can be used to evaluate cancer in general, without the need for an MRI. The ultrasonic examination is more practical and cheaper than other testing techniques including X-ray, CT, and MRI. Patients do not need to be concerned about radiation harm because it does not rely on radiation [9]. Using publicly accessible datasets, the goal of this study is to create completely autonomous CNN models with min-max normalization for many classifications of brain tumors. In the investigation of brain tumor diagnostic tests, the newly created EfficientNet CNN architecture can be a beneficial decision-making tool.

To improve accuracy, we have suggested a thick EfficientNet network for the categorization of three different types of brain tumors. It focuses on data enhancement using min-max normalization in conjunction with dense EfficientNet to improve training speed and network depth. To decrease the parameters and processing to a lesser extent, it comprises deep layers of separable convolution. Dense chain blocks must be added to the EfficientNet model in order to segment brain tumors, though. Consequently, dense EfficientNet may likewise attain very high classification accuracy. It gathers detailed picture data and creates dense segmentation masks to classify three different types of brain tumors. T1-weighted contrast-enhanced magnetic resonance imaging was used to assess it. Pre-processing, augmentation, and classification were used to gauge the network's performance. An innovative deep convolutional neural network-based dense depth classifier is given. Comparing the recommended methodology to existing deep learning techniques, it has a greater classification accuracy. As seen in the confusion matrix, the recommended technique offers great performance with less training samples. Because dropout layers reduce classification error, the overfitting problem is mitigated.

II. LITERATURE REVIEW

Hatami et al[15]. investigation looked towards combining image segmentation methods with a CNN pretrained model. A VGG-16 pretrained CNN model was recommended by Venkatesan Rajinikanth et al. [17] for the categorization of multigrade brain cancers. In 2010, ImageNet introduced the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC), a visual database initiative. This challenge offers a forum for several academics to assess the effectiveness of suggested approaches created on the provided picture collection in order to increase classification accuracy.

AlexNet, a CNN architecture, was suggested by Muhammed Talo et al. [4] to perform well on a variety of visual recognition-based applications. Lack of annotated picture datasets was the main barrier to the advancement of deep neural networks in the field of medicine. Applying a data augmentation strategy increases the number of data from readily available labeled picture datasets for a higher accuracy rate, which overcomes this. Weight sharing creates a sufficient impermeable network to do automatic illness prediction or detection using CT Scan brain pictures, and CNN-based transfer learning models achieved good performance.

III. METHODOLOGY

A. Symptoms of Tumors

Many of the many cancers that arise from primary tumors are difficult to identify in their early stages, sometimes discovered too late, and frequently miss the ideal window for therapy. Because of this, comprehensive early cancer diagnosis is crucial. The great majority of potentially cancerous early malignancies are often found on the micron scale by diagnostic testing for tumors. Early detection can prevent cancer from spreading and progressing, sparing the patient from the discomfort and life-threatening consequences that might otherwise result. Soft tissue sarcomas can be classified into four histological subgroups based on how differentiated the tumor cells are: highly differentiated, moderately differentiated, poorly differentiated, and undifferentiated [15]. The level of malignancy is higher and the level of differentiation is the lowest. The level of tumor differentiation varies, and doctors use a variety of subjective criteria when assessing a tumor's condition. The kind and location of the tumor are typically connected to the early signs of the tumor. Alterations in the anatomical makeup and histological morphology of the main lesion site brought on by the tumor's progression result in equivalent changes in symptoms.

The foundation for tumor inspection and diagnosis might be the development of tumors inside the tissue and the interaction between the tumor and surrounding tissue. For instance, early benign tumors may not show any symptoms at all. A patient's particular growth location is connected to a malignant tumor. In the early stages, the patient may only experience localized discomfort or swelling if the malignant tumor develops in a specific location. Because of this, each malignant tumor has a unique set of symptoms and growth areas. The early systemic symptoms of tumors are often moderate and restricted because the clinical presentations of benign and malignant tumors differ. Early identification of symptoms can aid clinicians in making timely treatment recommendations.

Since rapid diagnosis and treatment planning are crucial and can lower the mortality rate of cancer patients, early and precise diagnosis can assist medical professionals in making these decisions.

B. Background of Medical Facilities

A significant area of contemporary medicine is medical imaging technology, which is often employed in clinical settings, particularly for tumor diagnosis.

Digital X-ray radiography (X-ray), ultrasound color doppler (UCD), computed tomography (CT), and magnetic resonance imaging are examples of common medical imaging methods (MRI). By obtaining an organ sample and imaging it, doctors can make a quicker and more accurate diagnosis of a patient's illness. Improved treatment strategies can also I significantly lower the rate of misdiagnosis, (ii) increase the effectiveness of the overall healthcare system, and (iii) lessen the suffering of tumor patients.

The most direct method of communication between doctors and patients on their illnesses is medical imaging technology. The first and most popular kind of medical imaging examination among all types of high-precision medical equipment in hospitals is medical X-ray diagnostic equipment. X-ray pictures are much superior when examining subtle and dynamic lesions. Despite the recent development of new medical imaging technologies, X-ray diagnostic instruments continue to offer unbeatable benefits for bone, gastrointestinal, vascular, and breast exams. However, since the X-ray picture is the X-ray radiation's information carrier, it will unavoidably cause injury to the human body. Therefore, MRI is frequently utilized in clinical diagnostics due to its quickness and minimal danger of harming humans. Medical advancements have greatly advanced thanks to scientific research applications.

The density of bodily tissues may have an impact on the X-ray detection of breast and lung cancer cells in X-ray imaging mode. In UCD, the texture and density of bodily tissue may be determined using the resonance of sound waves. These pictures often display a tumor's or an organ's form. However, UCD often produces poor picture quality, making it challenging to acquire an accurate cancer area border and spot microscopic nodules.

A series of pictures captured by CT can indicate any localized horizontal slippage. The image's clarity reveals the organ tissue's density and structure.

Computer science is coupled with these imaging technologies to create computer-aided diagnostic systems.. It is a computer application for pathological diagnostics that aids in the calculation and detection of tumor lesions by integrating image analysis, medical image processing, and other potential biochemical and physiological methods. Medical pictures are typically captured by computer-aided diagnostic systems for tumor identification utilizing the right imaging technologies. The image is subsequently processed using a variety of software-based methods to isolate the distinctive tumor regions from the background. Shapes and textures, for example, can be derived from biomedical knowledge to create a feature space that defines the biometric properties of potential variation regions.

In computer-aided diagnostic systems, picture segmentation is crucial. It seeks to separate feature areas from the surrounding areas of the image. It may also integrate biological characteristics with visual characteristics like texture information to distinguish between various parts of an image. As a result, unaffected areas may be automatically filtered out, leaving behind suspect areas that share pathological traits such an uneven texture. For treatment planning, knowing the tumor's location and size as well as correct segmentation findings are crucial. Image segmentation, one of several medical imaging techniques, is a highly effective means to find cancer.

However, it is virtually inescapable that human involvement will be needed because to the variations in biological information at various places of the human anatomy. An expert doctor must supply the basic circumstances for setting categorization or training data. On the basis of data gleaned from medical imaging, multiple research have been conducted to identify distinct cancer kinds. However, the majority of image-based tumor diagnosis techniques only find a single tumor mold. The majority of image processing algorithms work with data from a single pattern or collection of photos. To improve feature recognition, such as tumor location and form, image processing extensions can integrate key characteristics retrieved from several modes of tumor pictures.

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C. Diagnostic Methods Based on Convolutional Neural Network

Clinical decision-making in the medical profession is supported by computer-aided diagnosis, which enables doctors to convert subjective picture input into objective image information. Convolutional neural network-based deep learning, however, provides clear advantages over conventional computer-aided diagnosis. Its extraction procedure is more straightforward, it can automatically extract information about distinguishing features from data sets, and its performance is more systematic and simpler to modify. Researchers can extract distinctive characteristics from the data that can be used to forecast cancer as machine learning and deep data mining make cancer diagnosis simpler.

Esteva et al. [17] trained a single convolutional neural network using inputs from picture pixels and illness labels to classify skin cancers. The 129,450 clinical photos that made up the training dataset for CNN. CNN exhibited a level of expertise equivalent to that of dermatologists by detecting keratinocyte carcinoma and benign seborrheic keratosis, the most prevalent cancer, and malignant melanoma and benign nevus, the worst skin cancer, and compared it with the diagnosis of dermatologists. In longitudinal CT investigations, Vivanti et al. [18] suggested automated liver tumor delineation based on a strong CNN technique for patient-specific and global CNN training on a small contour image dataset.. The approach suggested by the authors uses a subsequent frame structure to generate accurate tumor tracking through tiny training data sets, in contrast to other deep learning methods of medical image processing that call for a large number of annotated training data sets, somewhat alleviating the issue of manual processing. In order to accurately categorize two lung cancer subtypes, four bladder cancer biomarkers, and five breast cancer biomarkers, Khosravi et al. [19] built an independent pipeline incorporating numerous CNN-based computational algorithms. Three training methods are used in the pipeline classification, including CNN, Google's Inception, and the Inception and ResNet algorithms. The suggested technique distinguished distinct cancer tissues with accuracy of 100 percent in a wide range of tumor heterogeneity, 92 percent in subtypes, 95 percent in biomarkers.

1. Traditional Computer-Aided Tumor Diagnosis

Medical research has long centered on computer-aided diagnosis. Numerous computer-aided diagnosis technologies for various abnormal pictures continue to emerge and improve quickly, which is beneficial in that it significantly helps clinicians diagnose illnesses. First, medical images are inputted and segmented to produce multiple segmentation results for the same target region. Next, the feature segmentation results are extracted to create feature pools from which the first feature subset is then extracted. For each of them, the segment image results are created by using a variety of complimentary segmentation techniques on the same target region.

The following electronic databases were all used for the systematic literature search, and there were no language constraints The process of image classification is shown in figure 1. The search phrases include "Image feature Extraction," "Feature reduction," and "Traditional image classification," as well as their common, scientific, and synonym names. The search option may be used to find anything by manually looking up references for articles.

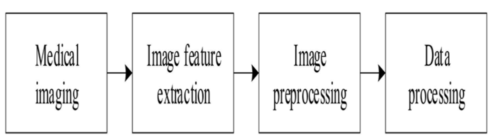

Figure 1 The process of image classification.

The computation can increase the efficacy of the feature information in the feature subset, lower the rate of false-positive detection in the classifier, and improve the precision of the diagnostic findings in computer-aided diagnostics system design.

D. Feature Extraction

The application of image processing technologies has grown significantly during the past several years. Some of these technologies are well developed and have produced wonderful results. The primary goal of image processing is to generate a wider range of applications through research on novel processing techniques. High precision, processing with rich information and flexibility, and complicated non-linear processing are all benefits of traditional digital image processing. The processing speed is slow for sophisticated processing, which is a drawback. Spatial and transform domain approaches make up the two types of digital image processing techniques. The two-dimensional functions are dealt with directly in the spatial domain method, which interprets the image as a collection of pixels on a plane. The image's orthogonality must first be transformed in order to modify the domain. The transform field's array of coefficients is then obtained, and different operations are carried out.

After processing, the space domain's inverse transformation is used to produce the processing outcome. Filtering, data compression, feature extraction, and other processing are examples of this sort of processing.
The primary focus of low-level feature extraction is on traits including texture, color, locality, and form. Scale-invariant feature transformation, accelerated robust feature extraction, quick orientation and rotation simplification, gradient direction histogram, and other techniques are frequently used for feature extraction.

IV. SYSTEM ARCHITECUTURE

A sizable dataset of 3260 different types of brain CT scan images was used in this investigation, and min-max normalization and data augmentation methods were applied [20]. The image database now includes 3064 T1-weighted, contrast-enhanced CT Scan images from Kaggle.com. The meningioma, which contains 708 photographs, the glioma, which has 1426 images, and the pituitary tumor, which has 930 images, are the three main forms of brain tumors. Three planes—coronal (994 pictures), axial (994 images), and sagittal (1025 images)—were used to collect all 233 patient images (1045 photos). The authors divided the dataset into three distinct regions for training, validation, and testing. The many stages of the proposed model are depicted in Figure 2.

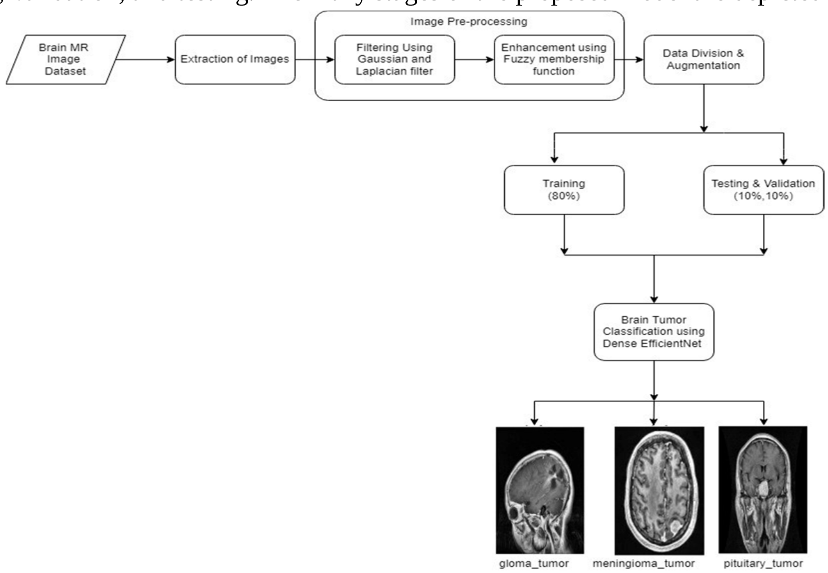

Figure 2 Overview of proposed dense EfficientNet methodology.

A. *Image Pre-Processing*

The images of brain tumors are of low quality due to noise and poor illumination. To make low pixel value images brighter, the recommended method applies data normalization, the min-max normalization function approach, followed by Gaussian and Laplacian filters. The original photographs were first given a Gaussian blur, and then the authors applied a weighted piece of the mask to take the blurred image out of it and produce the de-blurred image. In order to smooth the images shown in Figure 3 , a Laplacian filter with a kernel size of 3*3 was used.

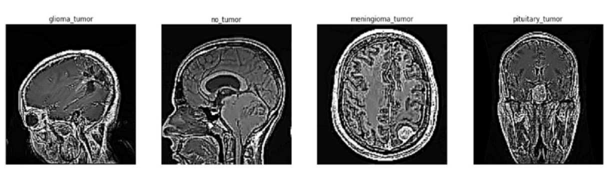

Figure 3 T1- contrast CT images of each label after filtration.

The CT Scan image, which was obtained from the patient's database, has uncertainty. These images also raise some questions. As a result, prior to further processing, brain pictures must be normalized. CT images frequently appear in grayscale. The pictures may therefore easily be adjusted to improve image quality and lower calculation error. Nayak et al. [21] integrated the morphological concept with the L membership function to detect brain tumors.
Figure 4 displays the final picture following the normalization.

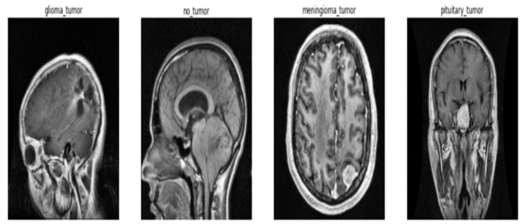

Figure 4.T1-contrast CT images of each label after fuzzification.

B. *Data Division and Augmentation*

Our dataset is little compared to what the deep neural network needs for better results. 3260 images of the brain make up our dataset, of which 80% are utilized for training and the remaining 20% for testing and validation. Therefore, data augmentation is necessary to make little modifications. The authors have employed rotation, width-shift, height-shift, and zoom—range to meet the data needs. The original data was enlarged 21 times for better training. The model will be able to learn more effectively by adding more training data. This could contribute to gathering more relevant data. It has the advantages of increased generality and decreased overfitting.. Data augmentation is the process of changing an existing dataset to include fresh samples (DA). On the original dataset, batch normalization, dropout regularization, and dropout through augmentation are used. Through data warping or oversampling, the size of the training dataset was increased.

C. *Dense EfficientNet CNN Model*

This paper offers a novel dense CNN model that combines dense layers and pre-trained EfficientNetB0. EfficientB0 has 230 layers and 7 MBConv blocks [22,23]. It features a thick block structure made up of four securely linked layers and a development rate of 4. For each layer in this structure, the input feature maps are the output feature maps of the layers below it. In EfficientNet, the dense block notion is represented by convolution layers of the same size as the input feature maps. By leveraging the output feature maps from the preceding convolution layers, dense block generates more feature maps with fewer convolution kernels. This CNN model was used to acquire the 150 x 150 enhanced CT scan image data. There is a distinct thick and drop-out layer.. The basic layer is called a dense layer, and each neuron in it receives one output from the layer below and sends one output to the layer above. The drop-out layer is used to reduce the network during training and avoid overfitting. We first add a pooling layer, then four thick layers, and lastly three drop-out layers to make sure the model runs smoothly. Each of the dense units has 720, 360, 360, and 180 neurons. The drop-out rates are 0.25, 0.25, and 0.5, respectively. Finally, to compute and categorize the probability score for each class, the scientists combined a Softmax output layer with a dense layer made up of four fully connected neurons. Figure 5 shows the proposed densenet model.

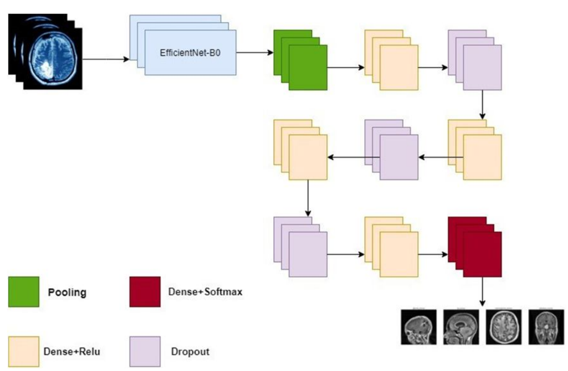

Figure 5 Proposed dense EfficientNet CNN model architecture.

V. SIMULATION AND RESULTS

A. *Results*

Numerous experimental assessments have been conducted to determine the suggested dense CNN model's validity. All the experimental evaluations have been conducted using a Python programming environment with GPU support. First, pre-processing is performed to enhance the contrast in MRI images using max-min normalization and then the images are augmented for training. The proposed dense-CNN model activated the augmented tumors for better accuracy

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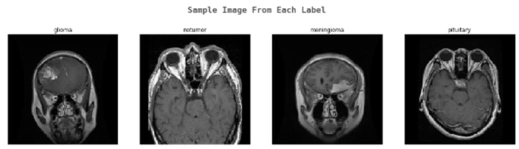
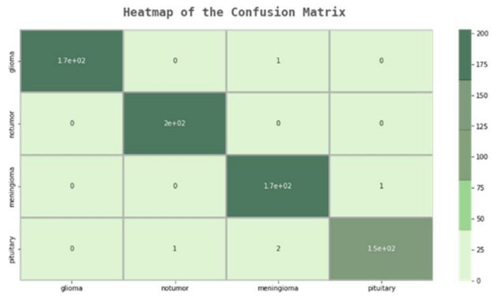
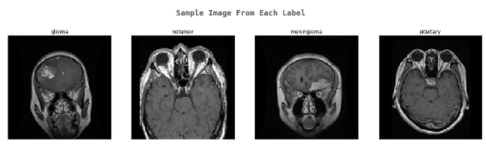
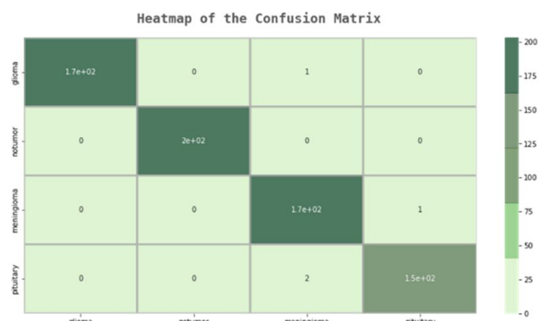
B. Number of epochs done on each model= 1



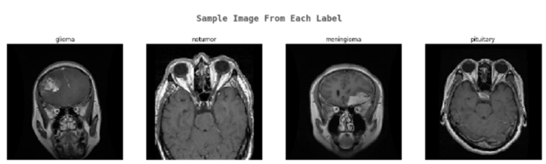


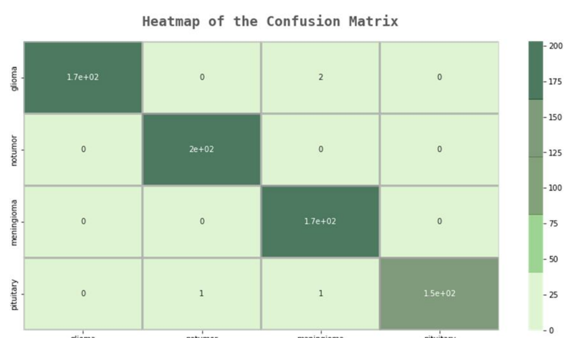
C. No of epochs = 5





D. No . of epochs = 25





VI. CONCLUSION

To categorize the various types of brain cancers with 98.78 percent accuracy in this study, the authors employed dense EfficientNet with min-max normalization, which is superior than previous comparable studies using the same dataset. In terms of accuracy, precision, and F1-score, the recommended strategy performs better than the current deep learning techniques. This hypothesis has been put out as a potential prognostic tool for brain tumor detection. Glioma has the lowest detection rate, with an F1-score of 98%, while pituitary has the greatest rate, with an F1-score of 100%, according to the research. Dense CNN has outperformed other deep learning techniques in terms of performance and classification accuracy. This technique is effective for quickly finding and identifying cancers.

Additionally, by adopting additional layers to segment the various medical picture segmentation, a better pre-processing approach may be used with the fuzzy thresholding idea or nature-based algorithms for early identification of dangerous medical imaging diseases. The focus of our future work will be on reducing the amount of parameters and processing time needed to execute the recommended model without compromising performance

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