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DEEP LEARNING BASED BRAIN TUMOR AND HEMORRHAGE DETECTION

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Abstract : Brain tumors and intracranial hemorrhages are serious medical conditions that can greatly impact the quality of life for patients. Early detection and diagnosis of these conditions are crucial for effective treatment and improved outcomes. So we came up with system to detect brain tumor and hemorrhage using deep learning techniques. This work uses Deep Learning (DL) architectures like Convolutional Neural Network (CNN) and EfficientNetB0 for Transfer Learning to detect the brain tumor.This model is used to predict the types of brain tumors .The model used to find brain hemorrhage is Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) layers, with LSTM and GRU layers, to extract features from the images and make predictions.

I.INTRODUCTION

Brain tumors and brain hemorrhages are severe medical conditions affecting the human brain. Brain tumors result from abnormal cell growth within brain tissue and are among the deadliest diseases globally, contributing to high fatality rates across all age groups. Early detection and treatment of brain tumors are crucial for reducing mortality rates. Symptoms vary based on the affected brain region and may include headaches, seizures, vision problems, vomiting, and cognitive changes. Brain tumors can be benign or malignant, with malignant tumors further classified into primary and secondary types.Brain hemorrhage, another life-threatening condition, requires immediate diagnosis and treatment. Brain Hemorrhage refers to bleeding between the brain tissue and the shull or inside the brain tissue.CT scans are the primary imaging tool for detecting hemorrhages, but manual interpretation by radiologists is time-consuming and error-prone. An automated system, utilizing deep learning techniques, can accurately classify CT scans as either hemorrhage or normal, enhancing diagnostic efficiency and patient care.Deep learning is a type of artificial intelligence that learns from data by replicating the structure of the human brain, using interconnected layers of algorithms called neural networks. In medical purposes, deep learning is utilized to analyze medical images, diagnose diseases, predict patient outcomes, and assist in drug discovery, among other applications.

II.LITERATURE REVIEW

In [1], CNN was used to categorize tumors. There are a total of 253 MRI scan images, 155 of them were tumors, while the remaining 98 are not. In this instance, training uses 80% of the data, whereas testing uses 20%. Depth wise Use of a Mobile net Architecture was used to implement separable convolutions. The accuracy detection rate for this work is 92%. This procedure can predict the presence or absence of a tumor.

In [2], There were 253 brain MRI images included in this data set, 155 of which are reported to have brain tumors, and 98 of which have no brain tumors. Radiation therapy, chemotherapy, and surgery are all possible methods of treating brain tumors. Here, CNN, support vector machines (SVM), and Artificial Neural Networks (ANN) were employed for the detection of brain tumors. This study consists of 80% of the total data, 10% of validation data, and the remaining 10% of testing data. In the future, 3D brain scans can be added to this work.

In [3], DL based methods for segmenting brain tumors include Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM). An algorithm for learning called the Extreme Learning Machine (ELM) consists of one or more layers of hidden nodes. Regression and classification were just two applications for such networks. In this study, a method for segmenting and classifying brain tumors was described. This work achieves 98.51% accuracy. Here many datasets were required and the procedure takes a very long time.

In [4], to get enough data for DL brain MRI images were enhanced. After that, the images were pre-processed to reduce noise and prepare them for subsequent processes. To create an image that is free of unnecessary features and to segment the tumor zone, auto encoders were utilized. KMeans is an unsupervised learning technique. Image augmentation is the process of enlarging the dataset by creating copies of the original images using various processing techniques, such as random rotation, shifts, shears and flips. 95.55% of the test data were accurate.

In[5],Comprehensive review covering etiology, clinical presentation, diagnosis, and management of intracranial hemorrhage.Discusses hypertension, cerebral amyloid angiopathy, trauma, and other risk factors.Reviews symptoms like headache, neurological deficits, and altered mental status.Emphasizes prompt imaging with CT and MRI for diagnosis.Covers medical interventions (blood pressure control) and surgical options (hematoma evacuation).Highlights significant morbidity and mortality associated with ICH.Stresses the importance of early recognition and multidisciplinary care in optimizing outcomes.

In [6] , This article discusses how doctors use different types of pictures, called imaging, to see inside the head and find bleeding in the brain.It talks about different ways doctors can take pictures of the brain, like CT scans and MRI scans, and how each method helps to find where and how much bleeding there is.The article helps readers understand what bleeding in the brain looks like on these pictures, and how doctors can use this information to figure out the best treatment for patients. By showing how imaging helps doctors diagnose and treat brain bleeding, the article highlights the importance of these techniques in providing better care for patients with intracranial hemorrhage.

In [7] ,This article talks about rules or instructions that doctors follow to treat people who have had a serious injury to their brain because of an accident or trauma. It explains what doctors should do at different stages of treating traumatic brain injury (TBI), including how to assess the injury, what tests to use, and what treatments are best.By giving clear instructions on how to care for people with severe brain injuries, these guidelines help doctors make the best decisions for their patients' health and recovery. They're like a roadmap that helps doctors know what steps to take to give patients the best chance of getting better after a serious head injury.

In [8], This research paper talks about a new way to use computer programs to find bleeding in the brain by looking at pictures of the head.The authors combined two different methods, called symmetric and standard deep convolutional representations, to create a better computer program for detecting brain hemorrhage. By improving how we use computer programs to find brain bleeding, this research can help doctors diagnose brain hemorrhages more accurately and quickly, which can lead to better treatment and outcomes for patients.

In [9], The paper discusses a method for helping doctors diagnose intracerebral hemorrhage (a type of bleeding in the brain) using computers. They combine two techniques: GLCM (Grey Level Co-occurrence Matrix) and CNN (Convolutional Neural Network). GLCM helps analyze images by looking at how different pixel values relate to each other, while CNN is a type of artificial intelligence that can learn patterns from images. By combining these two methods, the researchers aim to create a better system for diagnosing intracerebral hemorrhage accurately and quickly.

In [10], This paper from 2017 focuses on diagnosing different types of brain hemorrhages. They presented their findings at a conference called ICAC (International Conference on Advanced Computer Communication and Control). They discussed methods for classifying brain hemorrhages, likely based on analyzing medical images or data.

III.METHODOLOGY FOR BRAIN TUMOR

The Block diagram for the proposed methodology is shown in Fig .3.1

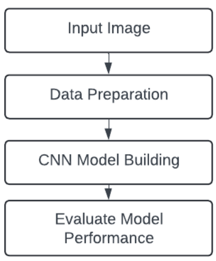

Fig.3.1: Block diagram of Methodology

Input Image: The image for this work is obtained through “Brain MRI Images for Brain tumor detection” dataset from Kaggle website.

Data Preparation: The dataset consists of four classes: Glioma tumor, No tumor, Meningioma tumor and Pituitary tumor respectively. The testing set contains 101 images of Glioma tumor, 105 images of No tumor, 128 images of Meningioma tumor and 99 images of Pituitary tumor. In the training set, there are 826 images of Glioma tumor, 397 images of No tumor, 825 images of Meningioma tumor and 827 images of Pituitary tumor. The sample images include classes of Glioma tumor, no tumor, Meningioma tumor and Pituitary tumor is shown in the below Fig.3.2

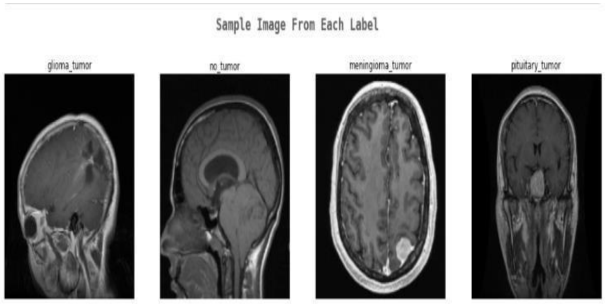

Fig.3.2: Samples of Images present in the dataset for brain tumor detection

Convolution Neural Network (CNN) Model Building: In this case, the CNN model is built using transfer learning and the EfficientNetB0 architecture.

Evaluate Model Performance: The performance of the model is evaluated by using the confusion matrix and classification report obtained from the model.

The CNN algorithm used here uses EfficientNetB0 architecture to classify the given input image.The architecture of the EfficientNetB0 model is shown in Fig .3.3. The EfficientNetB0 baseline model is employed as the entry point in this suggested technique, which accepts an input image with a dimension of 224x224x3. The mobile inverted bottleneck convolution (MBConv) and numerous convolutional (Conv) layers with a 3x3 receptive field are then used by the model to extract features from all of the layers. The primary rationale for using the EfficientNetB0 in this situation is that it has balanced depth, width, and resolution, which can result in a model that is scalable, accurate, and simple to install.

Fig. 3.3: EfficientNetB0 baseline model architecture.

EfficientNetB0 uses a fixed set of scaling coefficients to scale each dimension in comparison to other Deep Convolutional Neural Networks (DCNNs). This method outperformed previous cutting-edge algorithms developed using the ImageNet dataset. EfficientNet generated remarkable performance despite transfer learning, demonstrating its effectiveness beyond that of ImageNetNetB0 as a whole. The model had scales of 0 to 7 when it was first released, indicating an improvement in parameter size and even precision. Users and developers can now access and provide enhanced ubiquitous computing enhanced with DL capabilities across several platforms for a variety of applications thanks to the current EfficientNet. It is important to note that the focus of this work is the empirical investigation of contemporary DCNNs and EfficientNetB0 for the categorization of tumors kinds.

IV.METHODOLOGY FOR BRAIN HEMORRHAGE

.The block diagram for the proposed methodology is shown in Fig 4.1

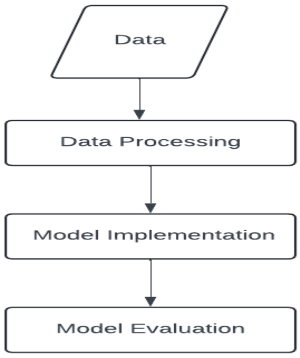

Fig 4.1: Block diagram of hemorrhage Data Collection

A.Data Collection

The dataset contains brain CT scan images that are categorized into two types: Normal and Hemorrhage.The Normal type of images refers to CT scans where there is no Brain Hemorrhage. There are 4105 Normal-type images in the dataset.On the other hand, Hemorrhage-type images refer to CT scans where bleeding is detected in the brain. There are 2690 Hemorrhage-type images in the dataset.The dataset contains 6794 files which include both hemorrhagic and normal brain CT scan images. The following images (Fig.4.2), (Fig.4.3) shows the amount of hemorrhagic and normal brain CT images available.

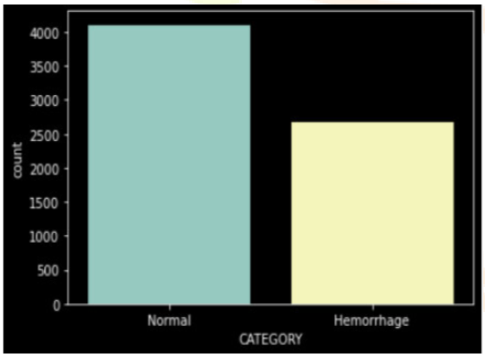

Fig 4.2: Image comparison

Fig 4.3: Image comparison

B.Data Processing

Setting of input data**:** We have decided to use the panda library to convert the dataset into a table format which will be containing 2 columns and 2 categories (Hemorrhage and Normal). We have categorized the Hemorrhage Type images as 0, and Normal as 1. We decided to remove the background image of all slices as it will not be of any use for classification and will only increase computational complexity. Moreover, we have converted all the images to JPG format as it is easier for PCs to read and will reduce space complexity and, reduce the load on our device while processing the images.

Training and testing Split**:** The train-test split is the cycle where the information split into a proper proportion for the train and the testing of the deep learning models. Our dataset is made up of only one type of image data which is CT Scan images of the brain while categorized as Normal-type images and Hemorrhage-type images. First, our dataset was split into train and test datasets. We split our dataset into a ratio of 9:1, where 6115 images were selected for training the data and, 680 images were selected for testing the data. Moreover, we Have decided to shuffle the dataset by setting the shuffle parameter to True for training quality.

C.Model Implementation

1. Input Layer: Accepts images of size (256, 256, 1).
2.Conv2D Layer: Extracts features using convolution with increasing filter sizes. Utilizes ReLU activation for computational efficiency.
3. Max Pooling: Reduces spatial dimensions of the feature maps.
4. Dropout Layer: Prevents overfitting by randomly dropping connections between neurons.
5. Time Distributed Flatten Layer: Prepares the data for time-series processing.
6. Bidirectional LSTM Layer: Processes data bidirectionally, capturing temporal dependencies.
7. Bidirectional GRU Layer: Further processes data bidirectionally with a different recurrent unit.
8. Flatten Layer: Converts multi-dimensional input into a single dimension.
9. Dense Layer: Fully connected layers for final classification, using ReLU and Softmax activations.

Each component plays a specific role in feature extraction, temporal processing, and classification within the model architecture.To summarize the achieved validation accuracy and loss can be considered valid test results.

V. ***RESULTS OF BRAIN TUMOR***

After implementing CNN algorithm for the dataset images the graph of accuracy v/s epochs and loss v/s epochs were obtained and it is plotted in Fig .5.1

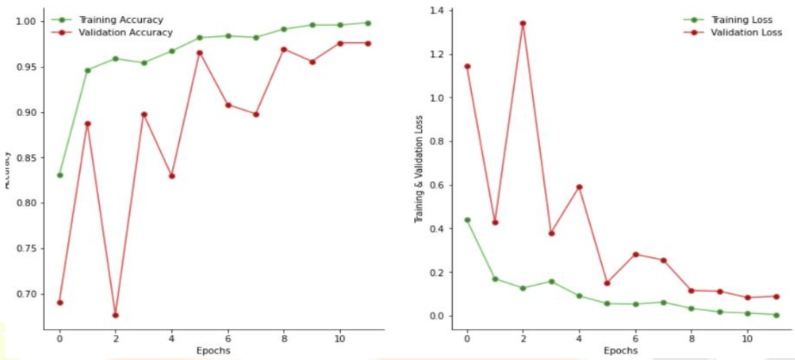

Fig .5.1: Graph of Accuracy v/s Epochs and loss v/s Epochs

These curves depict the model's performance over epochs during the training process. The accuracy curve illustrates how well the model improves its predictions as it learns from the training data, while the loss curve shows the decrease in the model's loss function over time. Analyzing these curves helps in understanding the model's convergence and potential overfitting or underfitting issues, guiding further optimization and fine-tuning of the brain tumor detection model.

Glioma Tumor	**94**	**0**	**3**	**0**
No Tumor	**0**	**48**	**0**	**0**
Meningioma Tumor	**1**	**0**	**93**	**0**
Pituitary Tumor	**0**	**0**	**0**	**89**
	Glioma Tumor	**No Tumor**	**Meningioma Tumor**	**Pituitary Tumor**

Table.1: Confusion Matrix obtain using the Convolutional Neural Network model

The model's performance was evaluated using a confusion matrix and classification report and it was found to be effective in identifying brain tumors with high accuracy.

VI.RESULT FOR HEMORRHAGE

In Fig.6.1, we see that both the loss and validation loss decrease over time. The loss measures how much our predictions differ from the actual values, Since the validation loss is lower than the training loss, it suggests that our model isn't overfitting**.** The validation loss goes down while the validation accuracy goes up. These metrics help predict how the model will work in the future Our training set's loss curve shows a decreasing trend, meaning our model is improving with each training step. Accuracy shows how well the model is learning and adjusting its parameters Our model's validation accuracy peaked at 94.%.We see that the validation accuracy, training accuracy, and validation loss follow similar trends, which is positive for handling new datasets.

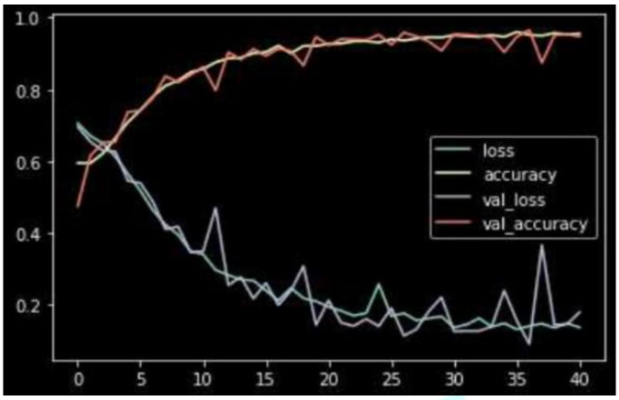

Fig.6.1: Summary plot

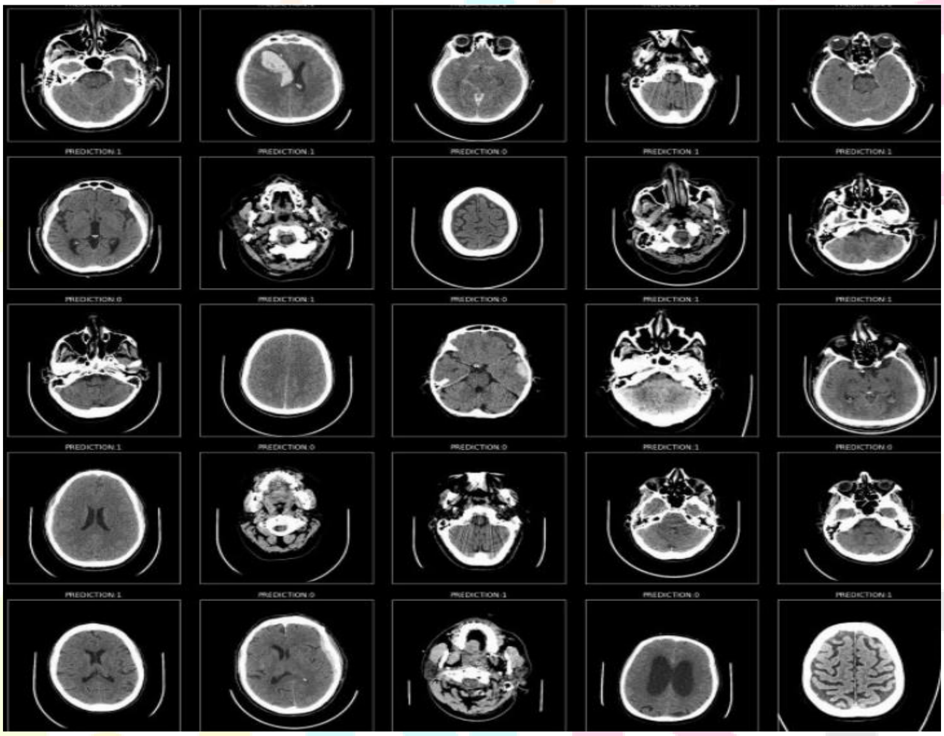

Fig.6.2: Image-set after prediction

Fig.6.2 shows the predictions generated by our model. Here, 0 indicates if a brain is affected by hemorrhage, while 1 indicates that the brain is normal.

VII.CONCLUSION

We studied brain hemorrhages using CT scan to identify them, a very important work because they are life-threatening. Our method was detailed and could be generalizable in other medical image analyses. Although our combined CNN-LSTM model was good enough, we suggest exploring reinforcement learning or batch size adaptation for better results. Convolutional neural networks are generally effective here,more research is needed into data selection and usage.

.Additionally, the identification of brain tumors is of great essence for avoiding complications. While MRI is the gold standard, it is complex making tumor identification difficult. We implemented a deep learning model based on EfficientNetB0 architecture with transfer learning as proposed by our study for brain tumor detection. The approach demonstrated excellent performance surpassing the ImageNet benchmarkings. Even if this contributes to automatic analysis of medical images, more future research needs to validate the models reliability across diverse datasets.

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