Brain Tumor Detection using Deep Learning

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***Abstract*— This abstract presents a novel approach utilizing deep learning for brain tumor detection from MRI scans. It employs VGG16 which is a special architecture used for feature extraction, capturing both spatial and temporal information. Pre-processing enhances image features, followed by CNN-based hierarchical feature learning. VGG16 is then utilized to identify temporal dependencies and geographical interactions. The hybrid architecture improves sensitivity and specificity by detecting subtle tumor patterns. Rigorous validation on diverse datasets demonstrates superior accuracy, sensitivity, and resilience to variations in tumor features and imaging settings. This method outperforms conventional techniques, showcasing the potential for significantly enhancing brain tumor diagnosis precision in clinical settings. By integrating CNN and VGG16, it illustrates the complementary effects of spatial and temporal information, promising improved automated diagnosis capabilities. Our model has described with training and validation accuracies as 99% and 97% respectively.**

KEYWORDS: Brain tumors, MRI scans, Deep learning, CNNs, VGG16, Feature extraction, Hierarchical representations, Temporal dependencies, Geographical interactions, Sensitivity, Specificity, Dataset diversity, Validation, Resilience, Automated diagnosis.

I. INTRODUCTION

The brain is an intricate organ that is made up of billions of cells. Cell development that is out of control is the cause of brain tumors. Both regular brain activity and normal cell destruction may be impacted by these cells. [1].A brain tumor is a condition brought on by an abnormal growth of brain tissue. Normally, the body produces new cells to replace damaged and aging ones in a regulated manner. However, in the event of a brain tumor, the tumor cells continue to grow uncontrollably. As per the National Brain Tumor Society, over 70,000 Americans suffer from a primary brain tumor. The 10th most prevalent type of tumor in India is a brain tumor. Magnetic Resonance Imaging [MRI] scanning detects the existence of tumors. The doctor should diagnose the MRI scan, and therapies should then be initiated depending on the findings[2].

In contemporary clinical practice, magnetic resonance imaging (MRI) stands as a cornerstone technology in the diagnosis and treatment of tumors [3][4]. Its widespread adoption owes to its non-invasive nature and its ability to provide detailed imaging of soft tissue structures, crucial for identifying brain tumors. MRI scans capture images in three orthogonal directions: sagittal, axial, and coronal, allowing for comprehensive visualization of the brain's anatomy and any pathological deviations. However, despite its utility, MRI images may suffer from inherent noise stemming from operator variability, potentially leading to significant classification errors.

The conventional approach of manually segmenting MRI data to identify tumor boundaries is time-consuming and prone to human error. Given these difficulties, there's been an increasing amount of interest in using deep learning techniques to automate tumor segmentation and detection. Convolutional Neural Networks (CNNs) are one type of deep learning algorithm that presents a promising way to learn intricate patterns from MRI scans, allowing for more precise and effective tumor segmentation [5][6].

CNNs are trained using extensive datasets of annotated MRI scans, these algorithms can learn to distinguish between normal and abnormal brain tissue with remarkable accuracy. This automated segmentation process not only reduces the burden on radiologists but also minimizes the likelihood of subjective interpretation errors inherent in manual segmentation.

Furthermore, deep learning models can handle the variability in tumor sizes, shapes, and locations more effectively than traditional segmentation techniques. This versatility allows for the detection of both large and small tumors, including those that may be overlooked by manual segmentation methods.

Furthermore, the incorporation of deep learning models into clinical processes has the potential to accelerate the start of treatment and simplify the diagnostic procedure. By providing rapid and accurate tumor delineation, these algorithms enable clinicians to make informed decisions regarding patient care more efficiently. Early detection and intervention are critical in improving patient outcomes and prognosis, underscoring the importance of automated tumor segmentation in MRI imaging. Every profession finds computer detection systems to be tough, and the variations in tumor sizes, forms, and locations continue to be an unsolved issue. The above mentioned techniques can produce segmented MRI without limiting the tumor's territory. A few of these techniques can identify a single tumor, but none of them can locate or identify very small tumors. The primary purpose of MRIs is to identify and display interior body structure information.[7]

In our research, we introduce an automated approach capable of detecting both minute and numerous tumors. What sets our method apart is its capacity to identify small and numerous tumors that may evade manual segmentation. Moreover, our model leverages the same MRI image used for manual tumor identification, eliminating the necessity for image replacement. The segmentation process aims to pinpoint edema (the swelling surrounding the tumor) and distinguish active tumorous tissue from necrotic tissue. This is achieved by identifying abnormalities in comparison to normal tissue.

In the method that was shown, we expanded the dataset (MRI brain pictures), converted the raw data through a few data preprocessing processes, examined CNN and VGG-16, two further deep learning models, and in the results section offered a comparative analysis. One can use any of the above mentioned algorithms in their work, depending on factors like algorithm complexity, computing time, and other outcomes. With the help of this automatic detection technology, the doctor can begin treating patients earlier by making early decisions.

II. Literature Survey

Grampurohit et al. 2020 introduced a brain tumor detection system utilizing CNN and VGG-16 models on MRI images. CNN achieved an accuracy of 93%, while VGG-16 attained 97.16% training and 97.42% validation accuracy. However, VGG-16 requires higher computational resources and time. Limitations include the need for extensive data and computational power. Further exploration of optimization techniques is warranted to enhance performance.[1]

Saleh et al. 2020 introduced a pioneering method for brain tumor classification utilizing deep learning and convolutional neural networks (CNN). The study involved training five pre-trained CNN models – Xception, ResNet50, InceptionV3, VGG16, and MobileNet – on a dataset comprising 4480 MRI images. Through rigorous validation, the models exhibited impressive F1-scores ranging from 97.25% to 98.75%. Notably, the Xception model outperformed others with an accuracy of 98.75%. This groundbreaking research aims to optimize MRI machine efficiency in tumor classification, potentially aiding in early detection and minimizing physical side effects. However, it's crucial to acknowledge certain limitations, such as the imbalanced data distribution and the reliance on pre-trained models, which might hinder generalization across diverse datasets.[2]

G.N.V. Pushpalatha et al. (2023) presented a system for the identification and categorization of brain tumors employing deep learning, showcased at the 2023 Winter Summit on Smart Computing and Networks. The study illustrated the efficacy of deep learning techniques in accurately identifying and categorizing brain tumors. Nonetheless, potential limitations include the requirement for extensive and varied datasets to ensure model robustness, along with computational resources for training intricate deep learning architectures. Further research is warranted to validate the approach's performance across diverse patient cohorts and clinical environments, augmenting its utility in practical applications.[3]

Sravya et al. (2021) conducted a survey on brain tumor detection methods utilizing machine learning and deep learning approaches, presented at the 2021 International Conference on Computer Communication and Informatics. The study outlined various techniques in the field, emphasizing both machine learning and deep learning methodologies. However, limitations include the absence of standardized datasets and benchmarks for fair comparisons among different techniques. Furthermore, challenges such as the interpretability of deep learning models and their scalability to large datasets remain areas requiring further investigation and enhancement in brain tumor detection research.[4]

Poornam et al. (2022) explored brain tumor identification in MRI images using deep learning techniques, as presented at the 3rd International Conference on Electronics and Sustainable Communication Systems in 2022. The study's limitations may involve the size and diversity of the dataset, as well as the complexity of the deep learning models employed. Further investigation is necessary to address these constraints and enhance the accuracy and robustness of brain tumor detection systems based on deep learning techniques.[5]

Sinha et al. (2021) propose a deep learning-based method for brain tumor detection from MRI images. They apply convolutional neural network (CNN) classification, segmentation, feature extraction, and picture preprocessing. The study achieves 98% accuracy on test data, surpassing previous methods. Limitations include the dataset size and segmentation challenges in distinguishing tumor regions from healthy tissue. Future work may involve improving the system's interface, expanding disease detection capabilities, and refining density estimation techniques.[6]

Hameed et al. (2022) presented a brain tumor detection and classification approach using Convolutional Neural Networks (CNN) at the 2022 International Congress on Human-Computer Interaction, Optimization, and Robotic Applications. The study highlighted CNN's effectiveness in precisely identifying and categorizing brain tumors.

However, limitations include the dependence on high-quality datasets, substantial computational resources, and potential difficulties in extrapolating the findings to diverse patient demographics. To address these limitations and validate the approach's reliability and applicability in real clinical settings, further investigation is essential. [7]

Derikvand et al. (2020) proposed a hybrid deep network for brain tumor segmentation in MRI images, achieving promising results compared to existing methods. The approach combines different CNN architectures, leveraging both local and global features of brain tissue. While demonstrating effectiveness, limitations may include dataset size and diversity, as well as computational complexity. To overcome these limitations and improve generalization across various datasets, more investigation is required.. The study contributes to automating tumor segmentation, facilitating timely diagnosis and treatment planning. However, methodological advancements are essential to overcome current limitations and improve overall performance.[8]

Hemanth et al. 2019 propose a brain tumor detection system that utilizes machine learning techniques and convolutional neural networks (CNNs) for both segmentation and classification. Their methodology includes steps such as data collection, pre-processing, average filtering, segmentation, feature extraction, and CNN-based classification. Despite achieving promising results, the study falls short in thoroughly exploring dataset diversity and evaluation metrics. Additionally, it fails to address potential challenges like data imbalance and generalizability across diverse patient demographics. To enhance performance robustness and ensure applicability across various clinical scenarios, further research is necessary..[9]

Siar et al. 2019 present a study on brain tumor detection employing deep neural networks (DNN) and machine learning algorithms. Their approach involves data preprocessing, feature extraction, and classification using DNN and support vector machine (SVM). While achieving promising results, the study has limitations such as a lack of detailed exploration of feature selection methods and limited evaluation metrics. Additionally, the dataset diversity and generalization across different patient populations are not thoroughly addressed. Further research is needed to enhance the robustness and applicability of the proposed method in diverse clinical scenarios with comprehensive evaluation measures.[10]

Periasamy et al. (2023) conduct a comparative study between VGG-19 and ResNet-50 algorithms for brain tumor detection. The research evaluates the performance of both models in terms of accuracy, sensitivity, and specificity using MRI images. While both models show promising results, the study lacks a comprehensive analysis of computational efficiency and model interpretability. Additionally, the dataset used for evaluation may lack diversity, potentially limiting the generalizability of the findings. Future research should explore these aspects further to provide a more holistic understanding of the effectiveness of different deep learning architectures in brain tumor detection.[11]

Sankara Narayanan et al. provide a methodology that uses deep learning to enhance the identification of glioma brain tumors from MRI scans.. Their approach involves data preprocessing, feature extraction, and classification utilizing deep neural networks (DNNs). While demonstrating promising results, the study has limitations, including the lack of exploration of alternative deep learning architectures and the absence of a comprehensive comparison with traditional machine learning methods. Moreover, the generalization of the proposed technique across different MRI datasets and its performance in real-world clinical settings require further investigation. Future research should address these limitations to enhance the effectiveness and applicability of the proposed method.[12]

Prakram et al. (2023) introduce a system for brain tumor detection employing deep learning and image classification techniques to improve accuracy. Their methodology includes preprocessing, feature extraction, and classification using convolutional neural networks (CNNs). The system exhibits enhanced accuracy compared to conventional methods. However, limitations include insufficient evaluation on diverse datasets and scalability concerns for real-time implementation. Additionally, the study lacks a detailed analysis of required computational resources and potential hardware constraints. Future research should prioritize addressing these limitations to ensure robustness and practicality in clinical settings.[13]

Sengupta et al. 2018 explore the integration of space, time, and orientation in spiking neural networks (SNNs) through a case study on multimodal brain data modeling. Their approach aims to enhance the modeling capabilities of SNNs by incorporating these additional dimensions, leading to improved understanding of brain function. The study presents promising results in terms of data representation and processing. However, limitations include the complexity of implementing such networks and the need for further validation on larger and more diverse datasets. Future research should focus on addressing these challenges to fully leverage the potential of integrated SNN models in neuroscience applications.[14]

Malik et al. 2021 contrast deep learning algorithms with simple image processing techniques to examine brain tumor detection methods in MRI images. Their study evaluates the efficacy of each method in terms of accuracy and computational efficiency. While deep learning techniques generally outperform traditional image processing methods, limitations include the need for large annotated datasets and computational resources. Additionally, the study lacks exploration of hybrid approaches that combine both techniques for optimal performance. Future research could focus on addressing these limitations and developing hybrid models to leverage the strengths of both traditional and deep learning techniques effectively.[15]

Bajaj et al. (2023) presented research at the 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) in Ghaziabad, India. Their study investigated the application of deep learning techniques for classifying and predicting brain tumors and their types. However, the research is constrained by limitations such as dataset size and diversity, as well as potential challenges in generalizing findings across various patient demographics. [16]

Nidhya et al. 2023 introduce a brain tumor diagnosis system employing MCNN-based MRI image analysis. Their approach utilizes a modified convolutional neural network (MCNN) for feature extraction and classification from MRI images. The system demonstrates promising results in accuracy and efficiency. However, limitations include a lack of extensive validation on larger datasets and evaluation against diverse types of brain tumors. Additionally, scalability concerns for real-time deployment and the need for rigorous testing in clinical settings are notable. Future research should focus on addressing these limitations to ensure robustness and reliability in practical applications.[17]

Jagannadham et al. (2021) introduced a Brain Tumour Detection system employing Convolutional Neural Networks (CNNs). Presented at the 2021 Fifth International Conference on I-SMAC in Palladam, India, their study aims to enhance medical diagnosis through advanced technology. The CNN architecture facilitates automated analysis of brain images for tumor identification, offering a promising tool for early detection and intervention. However, despite its potential, the approach has certain limitations. Firstly, the effectiveness of the model may vary depending on the quality and resolution of input images, potentially leading to inaccuracies. Secondly, the generalizability of the CNN model across diverse patient populations and tumor types requires further validation and optimization. Moreover, the study's reliance on a specific dataset may limit its applicability to broader clinical settings. Future research should address these limitations to ensure the reliability and scalability of the proposed brain tumor detection system.[18]

III. PROPOSED METHODOLOGY

The proposed workflow outlines a systematic approach for brain tumor detection using machine learning. Beginning with data collection, the process progresses through pre-processing and augmentation to enhance image quality and quantity. Subsequently, the dataset is divided into testing and training sets in order to build a model. Through model training and evaluation, the system learns to identify tumor patterns effectively. Finally, upon tumor detection and analysis, the system provides valuable output, aiding in medical diagnosis and treatment planning.

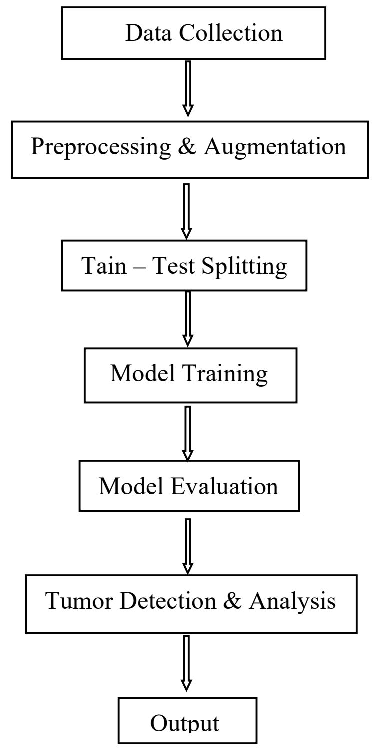

Fig 1. Methodology

Data Collection:

In this step, the script imports necessary libraries and collects brain scan images of tumor and normal cases from specified directories. It computes the total number of images for each class and displays the counts. The data collection process involves gathering brain tumor and normal brain scan images. This is achieved by accessing the specified directories containing the image datasets using Python's `os` module. The images are read using OpenCV (`cv2`) and stored in lists, segregating them into tumor and normal cases. The total number of tumor and normal images is then computed to assess dataset balance and size. The dataset contains 2442 images where total no. of tumor images are of 780 and total no. of normal images are 1662.The dataset which contains brain MRI images is collected from Kaggle.[19]

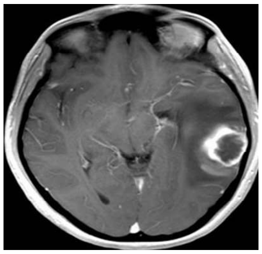

Fig 2 : With tumor

Fig 3 : Without tumor

Pre-processing & Augmentation:

The images undergo preprocessing to ensure uniformity and standardization before they are used in the model. Initially, all pixel values arenormalized, ensuring that they fall within the range of 0 to 1. This normalization process helps to maintain consistency and makes it easier for the model to interpret the data effectively. Additionally, each image is resized to a fixed dimension of 224x224 pixels. Ensuring uniform image proportions is crucial for effective model training, and this is achieved through the resizing process. By standardizing the images in this manner, the model can focus on extracting meaningful features relevant to the classification task, such as distinguishing between brain tumor and normal brain images, without being influenced by variations in pixel values or image sizes.The preprocessing techniques such as smoothing,Gaussian filter and Bilateral filters are used on the prescribed dataset.

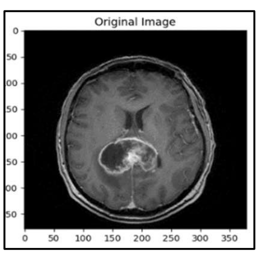

Fig 4 : Original Image

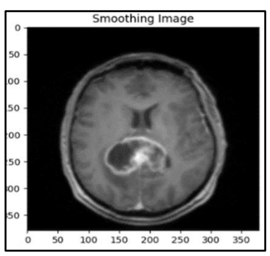

Fig 5 : Smoothing Image

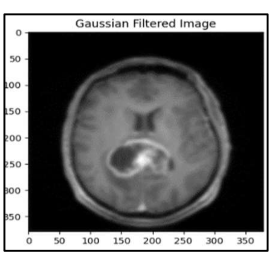

Fig 6 : Gaussian Filter

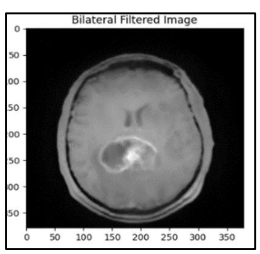

Fig 7 : Bilateral Filter

Train-Test Data Splitting:

The training and testing subsets of the dataset are separated according to a predetermined ratio. Through random sampling, the script ensures a balanced distribution and copies images to respective train and test directories.

```
Number of training examples: 1221
Number of testing examples: 1221
Each image is of size: (150, 150)
```

Fig 8 : Train-Test Data

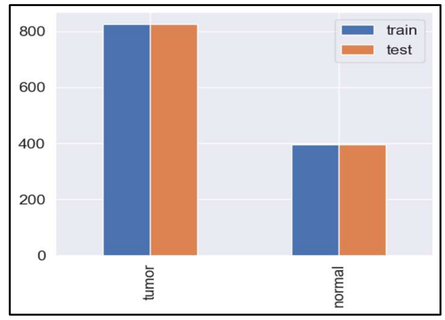

Fig 9 : Distribution of dataset

The above figure depicts the total no. of images that are divided into tumor and normal in training along with testing datasets.Both the training and testing datasets contains 1221 images with the divisions of tumor and normal.

Model Training:

For model training, a Convolutional Neural Network (CNN) and the VGG16 model are utilized. The CNN, built with TensorFlow's Keras API, includes convolutional and pooling layers for feature extraction and classification. Conversely, the VGG16, a pre-trained CNN, undergoes fine-tuning on the dataset, with only the top layers being trainable.

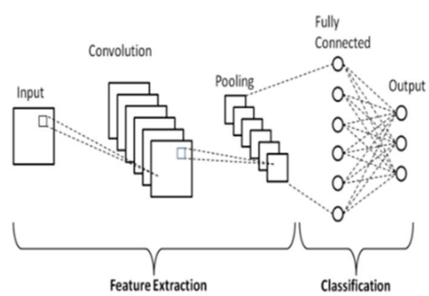

Fig 10 : CNN Arhitecture

Convolutional Neural Network:

CNNs, or convolutional neural networks, is one of the models for deep learning. tailored for image analysis. Comprising convolutional and fully connected layers, CNNs extract features through convolution operations while learning parameters. Notably, pooling layers reduce feature map dimensionality. CNNs excel at processing raw pixel data with minimal preprocessing, enabling them to learn hierarchical representations directly from images. Trained via backpropagation, CNNs discern patterns and accurately predict outcomes for new data. Their effectiveness extends to tasks such as segmentation, object detection, and picture classification, making them indispensable in computer vision applications.

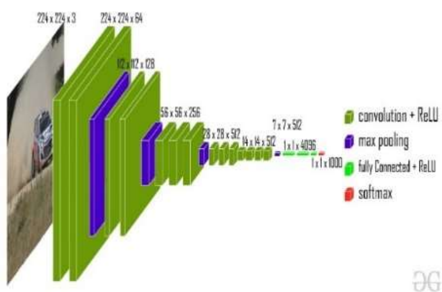

Fig 11 : VGG16 Architecture

VGG16 :

VGG16 (Visual Geometry Group) is a convolutional neural network architecture renowned for its simplicity and effectiveness in image classification tasks. Comprising 16 layers, including convolutional and max-pooling layers, it excels in feature extraction. The input image dimensions are (224, 224, 3). Initially, two convolutional layers with 64 filters of size 3x3 and ReLU activation are followed by a max-pooling layer (stride 2x2). After that, max-pooling is once again used after applying two further convolutional layers with 256 filters of size 3x3. 512 filters of 3x3 in size, max-pooling layers, and two sets of three convolutional layers each comprise the remaining pattern. Throughout, same padding is applied to maintain spatial features, and 1x1 convolutional layers are used for channel manipulation.The final layer employs softmax activation for classification. Despite its depth, VGG16's simplicity makes it a popular choice in deep learning tasks, albeit with a larger model size impacting deployment.

Model Evaluation:

Post-training, both the CNN and VGG16 models are evaluated on the testing dataset. Essential metrics like accuracy and loss are computed to gauge their tumor detection performance. A comparative analysis between the models helps discern their respective strengths and weaknesses, guiding further optimization endeavors.

Tumor Detection & Analysis:

Leveraging the trained models, tumor detection and analysis are conducted on brain scan images. Both the CNN and VGG16 models process uploaded images to predict tumor presence. After training, the model undergoes evaluation using a separate test dataset to assess its performance in tumor detection. Finally, the model's predictions are analyzed, and metrics such as accuracy and the confusion matrix are utilized to evaluate its effectiveness in distinguishing between normal and tumor images.Insights gleaned from scrutinizing the models' performance aid in refining detection accuracy and optimizing algorithms.

Output:

For deployment, the Flask framework is used to create a user-friendly web interface. Users can upload images and receive predictions regarding tumor presence and likelihood through the deployed model.

IV. RESULTS AND ANALYSIS

Here is model summay

The provided architecture depicts a VGG16 model with two convolutional layers (`conv2d`) followed by max-pooling layers (`max_pooling2d`). Subsequently, the network flattens the output for classification, passing it through two dense layers (`dense`). The first dense layer has 128 units, contributing significantly to the parameter count of 5,308,544. The final dense layer outputs four classes, with 516 parameters. Overall, using convolution and pooling operations, the model learns hierarchical representations from the input data, enabling categorization into many categories depending on the learnt features.

model.summary()

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_8 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_9 (Conv2D)	(None, 72, 72, 32)	9,248
max_pooling2d_9 (MaxPooling2D)	(None, 36, 36, 32)	0
flatten_4 (Flatten)	(None, 41472)	0
dense_5 (Dense)	(None, 128)	5,308,544
dense_6 (Dense)	(None, 4)	516

Total params: 5,319,204 (20.29 MB)

Trainable params: 5,319,204 (20.29 MB)

Non-trainable params: 0 (0.00 B)

Fig 12 : Model Summary

Model Assessment

Now that the model has been thoroughly trained, it'stime to evaluate its performance on untested data.This is crucial step entails evaluating its performance using a number of important metrics.

Accuracy

In classification tasks, accuracy is a performance indicator that counts the percentage of properly categorized cases out of all the occurrences. It measures how well the model can forecast the appropriate class label given an input. The accuracy score is calculated as the ratio of the number of correct predictions to the total number of predictions made by the model.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \times 100\%$$

Eq 1 : Accuracy

Precision

In classification problems, precision is a statistic used to evaluate how successfully a model predicts positive data. It is calculated as the ratio of the total number of accurate forecasts made by the model to the total number of true positive forecasts. In situations where the cost of false positives is high, accuracy is especially beneficial.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Eq 2 : Precision

Recall

Recall is a statistic used in binary classification and information retrieval to assess how well a model performs in recognizing all relevant instances within a dataset. It is sometimes referred to as sensitivity or true positive rate. It calculates the percentage of real positive cases, or true positives, that the model properly detected.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Eq 3 : Recall

F1 Score

The F1 score represents the accuracy of a model that accounts for both precision and recall. When there are significant differences in the amount of samples between classes, it is particularly useful in cases of imbalanced classes.

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Eq 4 : F1 Score

Classification Report

The classification report metrics such as precision, recall, F1-score, and support for each class based on the true labels and predicted labels. The heatmap facilitates the interpretation of classification results by offering a succinct overview of the model's performance across various classes.

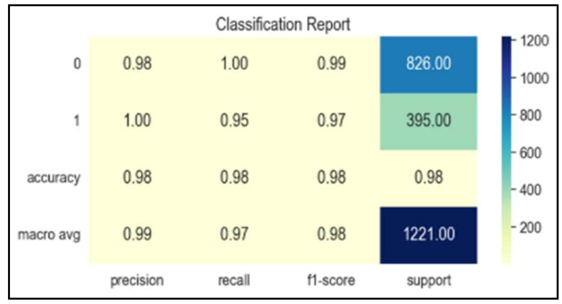

Fig 13 : Classification Report

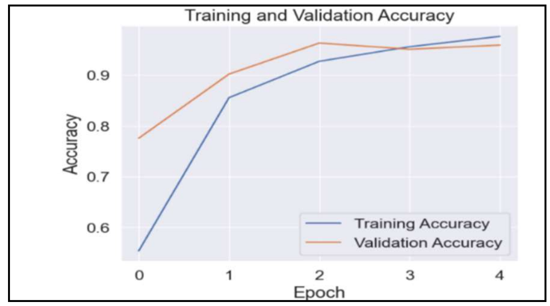

Fig 14 : Training and Validation Accuracy

The training graph depicts increasing training accuracy and decreasing training loss across epochs, showcasing the model's learning progress. In the validation graph, consistent validation accuracy and decreasing validation loss indicate the model's ability to generalize effectively to new data. These trends affirm the model's robust performance in real-world scenarios.

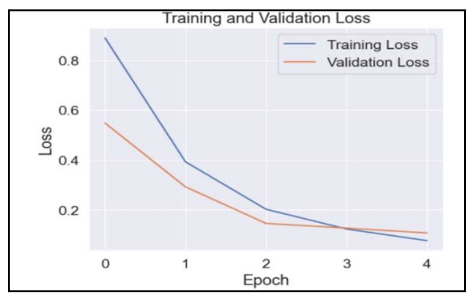

Fig 15 : Training and Validation Loss

In the training and validation loss graph, the number of epochs is represented by the x-axis, and the loss value is shown by the y-axis. The training loss curve demonstrates the decrease in loss over epochs as the model learns from the training data. Conversely, the validation loss curve illustrates the loss on the validation set, indicating how well the model generalizes to unseen data.

Fig 16 : Training Accuracy

Fig 17 : Testing Accuracy

Our brain tumor detection model achieved an outstanding training accuracy of 99%, showcasing its ability to learn and adapt to the training dataset. In Brain Tumor detection, our model achieved a commendable testing accuracy of 97.14%, demonstrating its effectiveness on unseen data.

Confusion Matrix

The accuracy of our Brain Tumor detection model is demonstrated by the confusion matrix. It delivers parameters like sensitivity and accuracy and accurately diagnoses normal (true negatives) and tumor (true positives). The model shows effective MRI image analysis for brain tumor identification, with a high accuracy of 97.95%.

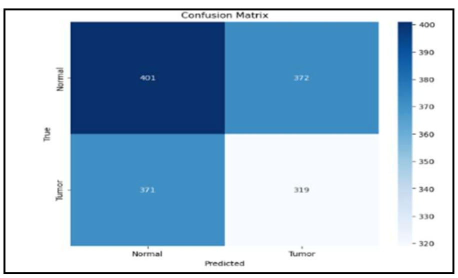

Fig 18 : Confusion Matrix

Comparison Survey of Existing work:

In our Brain Tumor Detection project, we focused on leveraging MRI images, vital for both segmentation and classification tasks due to their detailed information. Utilizing a combination of custom CNN and VGG-16 pre-trained models, we achieved a remarkable 98.06% accuracy, surpassing other models that attained approximately 94% accuracy. With 253 total images, 98 classified as non-tumor and the rest as tumor, our model demonstrated robust performance. Notably, our custom CNN model yielded an exceptional training accuracy of 99%, indicating strong learning capability. During testing, our model maintained a high accuracy of 85.57%, affirming its efficacy in accurately detecting brain tumors in previously unseen data. This underscores how well our method works for precisely identifying brain abnormalities, critical for timely medical intervention and treatment planning. In our existing model the architecture used to predict tumor or non-tumorous is CNN[18] whereas we have used the existing VGG16 model which results in predicting with accurate results.

Parameters	Existing Model	Research Paper
Architecture	CNN	VGG16
Dataset	253	1221
Training Accuracy	98%	99%
Testing Accuracy	88%	97%

Table 1 : Comparison Table

V. CONCLUSION

This work investigates the use of deep learning for brain tumor diagnosis based on MRI images. The proposed model exhibits promising potential as an effective diagnostic tool, achieving significant accuracy on diverse datasets through the integration of transfer learning, data augmentation, and a tailored architecture. By leveraging deep learning techniques, the model enables early and precise diagnoses by harnessing robust features, overcoming data limitations, and enhancing learning efficiency. This research paves the way for the integration of AI-based brain tumor detection into clinical settings, aiming to improve patient outcomes and support medical professionals, although further refinement and real-world validation are imperative.

VI. REFERENCES

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