BRAIN-TUMOR DISEASE DETECTION

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ABSTRACT

Brain tumors are among the most critical and life-threatening medical conditions, making early and accurate detection essential for effective treatment planning. The main objective of this project is to study the application of transfer learning using advanced deep learning architectures such as VGG-16, VGG-19, ResNet-50, Inception-V3, and DenseNet-201 for accurate and efficient brain tumor detection from MRI images. These models help address challenges like limited medical imaging data and high computational requirements. Traditional manual analysis of brain MRI scans is time-consuming and often affected by human subjectivity, which makes automated detection systems highly valuable. The proposed approaches utilize pre-trained deep learning models that are fine-tuned to classify brain tumor images effectively. Each model is evaluated using a benchmark dataset, with preprocessing techniques such as normalization, augmentation, and segmentation applied to improve feature extraction. Performance metrics including accuracy, precision, recall, and F1-score are used to assess and compare the models. Experimental results show that ResNet-50 provides the best performance due to its deeper architecture and strong feature extraction capability, followed by VGG-19 and Inception-V3. DenseNet-201 demonstrates a good balance between computational efficiency and accuracy, while VGG-16 performs reliably despite its relatively simple structure. This research highlights the effectiveness of transfer learning in overcoming challenges related to limited data and computational constraints in medical imaging. The findings provide valuable insights for deploying deep learning models in clinical environments, helping improve diagnostic accuracy and efficiency in brain tumor detection.

Keywords: *Brain Tumor; Transfer Learning; CNN*; *Accuracy; F1 Score*

1. INTRODUCTION

The brain is the most important and significant organ in the human body, however there are many others. Brain tumors are among the most frequent causes of brain impairment. Brain tumors are a serious health concern because they are characterized by aberrant and unchecked cell proliferation within the brain. Brain failure occurs when brain tumor cells proliferate to the point where they eventually absorb all the nutrition intended for healthy cells and tissues. These tumors, whether primary brain tumor (benign) or secondary brain tumor (malignant), pose severe risks to patients due to their potential to disrupt critical brain functions such as memory, cognition, vision, and motor control. Early and accurate diagnosis is imperative to mitigate these risks and to improve the likelihood of successful treatment outcomes. The conventional method of tumor identification is predominantly based on the visual analysis of medical images conducted by trained professionals, a process that may be subjective and susceptible to error. New AI-powered methods for analyzing brain tumors have been possible in recent years due to developments in deep learning, which may increase efficiency, accuracy, and objectivity [1]. The development of robust and efficient diagnostic methods is an essential focus of modern medical research. Among the various imaging techniques available, Magnetic Resonance Imaging (MRI) is widely regarded as the gold standard for brain tumor detection [2]. MRI offers exceptional resolution and contrast, making it particularly effective for visualizing the complex anatomy of the brain and identifying abnormalities [3]. Despite its advantages, the accurate interpretation of MRI scans remains a challenge due to the variability in tumor size, location, and morphology, as well as the expertise required for manual diagnosis. These restrictions have increased the demand for intelligent and automated technologies that can help with brain tumor identification and categorization.

Medical image analysis has changed as a result of the advent of deep learning (DL) [4], especially Convolutional Neural Networks (CNNs). CNNs automatically extract pertinent features from unprocessed images, in contrast to conventional machine learning techniques that depend on manually created features. Significant progress has been made in tasks including picture classification, segmentation, and anomaly detection as a result of this end-to-end learning capabilities [5]. However, the application of CNNs to brain tumor detection is not without challenges. Limited datasets, high computational demands, and the risk of over-fitting are persistent hurdles that researchers must address to achieve reliable and generalized results.

The study emphasized the importance of transfer learning in mitigating the challenges posed by limited dataset sizes [6]. The authors explored the use of pre trained deep CNN architectures, including VGG-16, VGG-19, ResNet50, Inception-V3, and DenseNet-201 to classify brain MRI images [8]. The success of pre-trained models highlights their potential to leverage knowledge from diverse domains and apply it to specific problems with limited data availability. Moreover, the use of data augmentation techniques further enhanced the performance of these models, enabling them to generalize better to unseen data.

Despite the progress made in applying deep learning techniques to brain tumor classification, several challenges remain unaddressed: Data Scarcity: The availability of high-quality, annotated MRI datasets [9] is limited, which can hinder the training of deep learning models. Variability in Tumor Characteristics: Tumors differ significantly in terms of size, shape, location, and intensity, making it difficult to develop a one-size-fits-all model. Computational Complexity: Deep CNNs require substantial computational resources, particularly during training, which can be a barrier for re searchers with limited access to high-performance hardware.

Generalizability: Models trained on specific datasets may not generalize well to new data, reducing their clinical applicability. This project aims to address these challenges by developing a robust deep learning framework that leverages transfer learning, data augmentation, and f ine-tuning techniques to improve the accuracy and generalizability of brain tumor classification models.

The current research runs with the motto of examine the effectiveness of pre-trained deep learning models for brain MRI image categorization, such as VGG-19, ResNet50, Inception-V3, and DenseNet-201. Use data augmentation strategies to improve the training dataset's resilience and diversity. To adjust pre-trained models to the unique needs of brain tumor classification, optimize the fine-tuning procedure. Evaluate the models using comprehensive performance metrics, including accuracy, precision, recall, and F1 score, on both training and test datasets. Compare the results with state-of-the-art methods and identify areas for further improvement.

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The current research focuses on the critical and life-threatening condition of brain tumors. While several studies in recent years have explored various machine learning algorithms for tumor detection and classification, this work distinguishes itself by employing ResNet-50 and DenseNet-201 models, achieving comparatively higher accuracy than previously reported methods.

2. LITERATURE SURVEY

Brain tumor detection involves identifying abnormal brain growths using a variety of medical imaging techniques, diagnostic tests, and clinical evaluation. Early detection is crucial to improving the health condition of patients. Primary methods for detecting brain tumors include magnetic resonance imaging which provides detailed brain images, detecting small tumors, with advanced techniques such as fMRI and contrast-enhanced MRI offering additional information. The PET scan identifies abnormal activity as tumors consume more glucose. MRS is an advanced magnetic resonance imaging technique that analyzes brain tissue composition to differentiate tumor types. Another method includes a neurological examination in which doctors per form an evaluation of symptoms such as persistent headaches, seizures, vision changes, nausea, cognitive problems, and motor impairments. Using neurological tests, these tests evaluate reflexes, motor skills, coordination, balance, and cognitive abilities to identify any dysfunction caused by a potential tumor. The next type of detection is the use of biopsy. Stereotactic biopsy, in which if the imaging suggests the presence of a brain tumor, a biopsy may be performed to confirm the diagnosis. A small tissue sample is removed from the tumor to be analyzed for cancer cells. In Intra-operative Biopsy, biopsies are taken during surgery to remove the tumor allowing for real-time diagnosis and treatment planning. There are some Advanced Imaging Techniques in which Diffusion Tensor Imaging (DTI) is a type of magnetic resonance imaging that maps white matter tracts in the brain that are useful in tumor surgery planning. Functional MRI (fMRI) maps brain activity by detecting changes in blood flow that helps to determine tumor location relative to functional brain areas. Magnetic Resonance Angiography (MRA) is a specialized MRI that examines blood vessels in the brain that may be involved if a tumor that affect the blood flow. Nowadays Artificial Intelligence (AI) in Brain Tumor Detection is mainly used to detect brain tumor. AI technologies particularly machine learning algorithms that are increasingly being used to help detect brain tumors from medical images. These systems can analyze MRI and CT images, sometimes identifying tumors faster and with greater accuracy than human radiologists. They can also help with the classification and grading of tumors providing insights into treatment options.

The key steps in brain MRI image classification includes data collection, pre processing, modal architecture, training the model, model evaluation, post processing, tumor classification and model deployment. Deep learning, a subset of machine learning, has revolutionized the field of medical image analysis, particularly in the detection of diseases. Among various deep learning techniques, Convolutional Neural Networks (CNNs) are most commonly used due to their ability to automatically extract features from images, eliminating the need for manual feature extraction. CNNs have demonstrated exceptional performance in tasks such as image classification, segmentation, and object detection, all of which are crucial for brain tumor diagnosis.

Abbasi et al., [1] conducted a study on advancements in the use of deep learning for stroke lesion segmentation in both MRI and CT scans to justify which modality is superior for brain ischemic stroke detection. The utilization of deep learning techniques, particularly convolutional neural net-works (CNNs) and U-Net-based models has shown great promise in detection of brain ischemic stroke in accurately and automatically segmenting. By learning from extensive datasets, these models are able to manage the complexity and diversity of stroke lesions with ease. The pooled lesion-wise dice score, patient-wise sensitivity, and lesion-wise sensitivity were computed using a random-effect model. Amin et al. [11] developed a model that used a multi-stage deep learning framework for detecting and segmenting brain tumors in MRI scans. Their method incorporated a U-Net-based architecture, specifically designed for image segmentation tasks, and showed robust performance in segmenting tumor regions, even in cases of irregular tumor shapes. The study emphasized the importance of accurate segmentation for effective diagnosis, as it enables better understanding of the tumor's size and location, which are critical for treatment planning. The quality and variability of MRI images can significantly affect the performance of deep learning models. Many studies have incorporated preprocessing steps such as normalization, noise reduction, and skull stripping to enhance the quality of MRI images before feeding them into a neural network. Wang et al. [12] proposed the use of preprocessing techniques such as histogram equalization and image resizing to standardize input images, improving the model's ability to generalize across diverse datasets. Data augmentation, such as random rotations, scaling, and flipping, has also been widely used to artificially increase the size of training datasets which helps prevent over-fitting and improves the robustness of the model.

In recent years, VGG-19 has gained popularity in medical image analysis, especially in fields such as radiology, pathology, and neuro imaging. Researchers have leveraged VGG-19's capacity to extract deep features for tasks such as tumor detection, segmentation, and classification. P. Wang et al. [15], VGG-19 was applied to classify brain tumor images from MRI scans. The study demonstrated VGG-19's effectiveness in detecting and classifying different tumor types, including gliomas and meningiomas, achieving high accuracy in differentiating between malignant and benign tumors. In breast Cancer Detection Abuared et al. [16] was used VGG-19 to classify mammogram images for breast cancer detection. The model was fine-tuned on a breast cancer dataset and showed a promising performance, highlighting the potential of VGG-19 in automating the analysis of medical images, where manual interpretation can be time-consuming and error-prone. Transfer learning, where a pre-trained model is fine-tuned on a different but related task, has become a powerful technique in deep learning. VGG-19, pre-trained on large image datasets like ImageNet, has been widely used in various domains with limited data for the target task. S. Ahmad et al. [18] demonstrated the power of transfer learning using VGG-19 in the context of skin cancer detection. The model was fine-tuned on a dataset of dermoscopic images to detect malignant melanomas. The fine-tuning process with transfer learning enabled the model to perform well despite the limited availability of annotated skin images, achieving high classification accuracy. M. Agn et al. [7] envisaged VGG-19 for medical image classification tasks where labeled data is scarce. By freezing the initial layers of the pre-trained VGG-19 and training only the fully connected layers, they were able to build a reliable classification system with limited data, which is a critical advantage in medical imaging where acquiring large labeled datasets can be challenging.

The paper on intelligent system using U-Net with residual networks for segmentation and YOLO2 for classification of brain tumors in MRI images [19] in which the system achieves high accuracy and sensitivity. The system reached an accuracy of 99.60% for segmentation and 97% for tumor classification. Tabatabaei et al., [28] demonstrated that applying data augmentation techniques to their CNN model significantly improved the model's ability to generalize, leading to better performance on unseen MRI scans. They proposed a novel method that combines local and global features derived from CNNs and TMs to improve classification ac curacy through a cross-fusion strategy. Additionally, a two-branch parallel model that integrates the Transformer Module (TM) with the Self-Attention Unit (SAU) and Convolutional Neural Networks (CNN) was presented in order to classify brain tumors in MR images. A lightweight and enhanced CNN architecture (ResNet) has been created in addition to their work, and it can identify tumor features from MR images. Twenty percent of the 3064 slices of the dataset's four-class MR images were deemed unseen. For testing, validation, and training, the remaining portion was split into 60%, 20%, and 20% slices. The accuracy of VGG, DensNet, and ResNet is 98.59%, 98.94%, and 99.30%, respectively, when the overall structure is merged with other comparable CNN networks.

3. METHODOLOGY:

3.1 Introduction: The methodology for this project is designed to achieve the above objectives systematically. Dataset Preparation: MRI datasets are pre-processed to ensure uniformity in image resolution, intensity normalization, and removal of artifacts. Rotation, flipping, and contrast adjustment are examples of data augmentation procedures used to expand the dataset's size and diversity. Model Selection: Pre-trained models such as VGG-19, ResNet50, Inception V3 and DenseNet-201 are selected for their proven performance in image classification tasks. These models are fine-tuned using transfer learning to adapt to the specific task of brain tumor classification. Training and Evaluation: The models are trained on the preprocessed dataset using a carefully designed training pipeline. Important hyper parameters are adjusted to avoid over-fitting and enhance generalization, including learning rate, batch size, and epoch count. Performance is evaluated using metrics such as accuracy, precision, recall, F1 score, and confusion matrices. Comparative Analysis: To evaluate the efficacy of the suggested strategy, the outcomes are contrasted with current techniques from the literature. Insights are drawn from the analysis to identify strengths and limitations.

The techniques and resources used in this work to classify brain MRI images into tumorous and non-tumorous categories are thoroughly explained in this chapter. The primary goal of this research was to develop an accurate, automated classification system that could assist medical professionals in diagnosing brain abnormalities efficiently. The chapter begins with a description of the dataset utilized, detailing its source, composition, and the challenges posed by its limited size and class imbalance. Next, the preprocessing techniques applied to the dataset are discussed, including steps such as cropping, resizing, and normalization, which were essential to standardize the images and enhance the training process. Data augmentation strategies are also elaborated upon, as they were critical in enriching the dataset and addressing the issue of over-fitting caused by the small dataset size. The implementation of advanced deep learning models, namely VGG-19, VGG 16, ResNet50, Inception-V3 and DenseNet-201, forms a significant part of the study. The choice of these models is justified by their proven effectiveness in image classification tasks and their adaptability to transfer learning. Transfer learning played a pivotal role in this study, enabling the use of pre trained models to achieve high accuracy with minimal training data. Finally, the chapter describes the evaluation matrices used to measure the performance of the models, ensuring a robust and fair comparison. Each step of the methodology was meticulously designed to maximize accuracy and minimize errors, reflecting the scientific rigor underpinning this research. This study lays the groundwork for a dependable system that could help with the early diagnosis of brain tumors and potentially improve patient outcomes by fusing cutting-edge methods in data processing, augmentation, and deep learning.

3.2 Dataset Description: The dataset is readily available on open source website called, Kaggle.com and https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection. The dataset utilized in this study comprised a total of 305 brain MRI images, sourced from publicly available online repositories. These images were classified into two distinct categories: tumorous and non-tumorous. Among the collected images, 155 belonged to the tumorous category, representing brain MRI scans that displayed the presence of tumors, while the remaining 150 images were labeled as non-tumorous, indicating the absence of any abnormal growth or tumor in the brain. The dataset's relatively small size posed a significant challenge in achieving robust and generalized model performance, especially considering the field of medical imaging often requires large datasets for training deep learning models effectively. Furthermore, the dataset was inherently imbalanced, with a slightly higher number of tumorous images than non-tumorous ones. This imbalance could lead to a bias in the classification process, where the model might favor the dominant class, thus affecting its ability to perform accurately on unseen data. To address these challenges, data augmentation techniques were employed to artificially expand the dataset and balance the representation of both classes. Augmentation is a widely used method to enhance small datasets by generating new, modified versions of existing images. In this study, several augmentation strategies were applied such as rotation, Horizontal and Vertical Shifting, Rescaling, Axis Mirroring. These changes were carefully chosen to replicate true fluctuations that could arise during MRI imaging, enhancing the model's resilience and capacity for generalization. For instance, slight rotations or positional shifts can simulate natural differences caused by patient movement or variations in MRI machine settings. After applying data augmentation, the dataset was effectively balanced, ensuring equal representation of both tumorous and non-tumorous images. This balance is crucial for reducing classification bias and enabling the model to perform well on both categories. Additionally, the diversity introduced through augmentation techniques enriched the dataset, allowing the model to learn a wider range of features and patterns associated with brain MRI images. Overall, the dataset preparation and augmentation steps laid a strong foundation for the subsequent phases of preprocessing, training, and evaluation, ensuring that the deep learning models were provided with high-quality and representative data for optimal performance.

3.3 Image Preprocessing: To ensure the raw MRI images were suitable for training deep learning mod els, a series of preprocessing steps were applied. These steps aimed to standardize the input data, remove irrelevant features, and optimize the images for efficient processing. Preprocessing is a critical step in any image-based machine learning task, as it minimizes noise, reduces computational over head, and improves model focus on the region of interest. In this study, preprocessing included cropping, resizing, and normalization, each of which played a vital role in preparing the dataset.

3.3.1 Cropping and Border Detection: The first step in preprocessing involved cropping the raw MRI images to remove unnecessary background information, such as black borders or irrelevant regions outside the brain tissue. These extraneous features can intro duce noise, distract the model, and reduce classification accuracy. Using the OpenCV library, a robust and efficient computer vision tool, the boundaries of the brain tissue were automatically detected in each image. The algorithm identified the polar points of the brain tissue, defining the cropping region to isolate the brain. This process not only removed irrelevant portions of the image but also ensured that the resulting dataset focused exclusively on the brain's structure. By eliminating the black borders and external artifacts, this step reduced the complexity of the data and allowed the models to concentrate solely on the relevant features. Consequently, the cropped images provided a cleaner and more precise representation of the brain's anatomy, facilitating better feature extraction and analysis.

3.3.2 Resizing and Normalization: Once the images were cropped, they were resized to a uniform dimension of 224 × 224 pixels. This resizing step was essential for standardizing the dataset and ensuring compatibility with the input size requirements of the pre-trained deep learning models used in the study, such as VGG-19, ResNet50, and others. Maintaining a consistent image size across the dataset is crucial for batch processing and reduces computational inefficiency during model training. In addition to resizing, the pixel intensity values of the images were normalized. Normalization involved scaling the pixel values to fall within a range of 0 to 1 by dividing each pixel value by 255. This transformation helped to standardize the input data and reduce variations caused by differences in image intensity. By ensuring that all pixel values were on a similar scale, normalization prevented certain features from disproportionately influencing the model, thereby improving the training process.

3.3.3 Importance of Preprocessing: Together, cropping, resizing, and normalization addressed several challenges inherent to the raw dataset. Cropping ensured the exclusion of unnecessary background noise, resizing standardized the input dimensions for compatibility, and normalization improved model convergence by reducing numerical disparities. These preprocessing steps collectively enhanced the quality of the input data, allowing the deep learning models to focus on the critical features of the brain MRI images. By implementing a robust preprocessing pipeline, the study ensured that the dataset was clean, consistent, and optimized for training. This meticulous preparation provided a strong foundation for the subsequent steps of data augmentation, training, and model evaluation, contributing to the overall success of the classification system.

3.4 Deep Learning Models: Medical image analysis has been completely transformed by deep learning, which provides automated feature extraction and categorization with previously unheard-of precision. Four cutting-edge pre-trained deep learning models-VGG-19, VGG-16, ResNet50, Inception-V3, and DenseNet-201 were used in this study to identify the brain MRI data. Because of their demonstrated effectiveness in picture classification tasks and their capacity to utilize pre-trained weights from sizable datasets, these models were selected. The study sought to create a reliable method for identifying brain pictures that were tumorous or non-tumorous by using these models.

3.4.1 Transfer Learning: A key component of this research was the utilization of transfer learning, a method that allows models trained on large datasets to apply their expertise to new but related tasks. In fields where there are frequently few large labeled datasets available, such as medical imaging, transfer learning is especially beneficial. The convolutional layers of the pre-trained models were frozen in this method, maintaining their capacity to extract significant features from pictures, including edges, textures, and patterns. These layers served as feature extractors, and only the final, fully connected layers of each model were adjusted to meet the unique requirements of the brain tumor classification task. This method decreased the risk of over-fitting, which is typical when deep models are trained on limited datasets, in addition to cutting down on training time and computing expense

3.4.2 Model Architectures: Each of the five models had distinct architectural features that made them suitable for the task at hand:

3.4.2.1. VGG-19: Three fully connected layers and sixteen convolutional layers make up the 19 layers of the deep convolutional neural network VGG-19. It uses a uniform architecture, where all convolutional layers are designed with 3 × 3 filters and a stride of 1. The simplicity of this design allows the model to focus on feature extraction without introducing unnecessary complexity. The fully linked layers manage the final classification, whereas max-pooling layers minimize spatial dimensions. VGG-19 is known for its robustness in identifying intricate image patterns.

3.4.2.2. VGG-16: A simpler variant of the VGG family, VGG-16 comprises 16 weighted layers. It maintains the same uniform convolutional filter size as VGG-19 but reduces the depth of the network, making it computationally less intensive. VGG-16 strikes a balance between performance and efficiency, making it a popular choice for tasks with moderate computational resources.

3.4.2.3. ResNet50: ResNet50 is part of the residual network family, featuring 50 layers with a unique approach to training deep models. It introduces residual connections, which help bypass some layers, allowing the model to learn residual functions instead of direct mappings. This architecture effectively addresses the vanishing gradient problem, enabling the training of very deep networks without a loss in performance. The residual blocks enhance the model's ability to learn complex features without degradation.

3.4.2.4. Inception-V3: Inception-V3 employs a 42-layer architecture designed to handle multi-scale feature extraction using inception modules. Each module applies multiple filter sizes (e.g., 1 × 1, 3 × 3, and 5 × 5) in parallel, enabling the model to capture fine and coarse details simultaneously. Additionally, auxiliary classifiers are used to prevent gradient vanishing during training. Inception-V3 is particularly suited for extracting diverse features from complex images, making it a valuable asset in image analysis.

3.4.2.5. DenseNet-201: A convolutional neural network (CNN) having 201 layers, DenseNet-201 is capable of classifying images into 1,000 different object categories. It was created in 2017 by Facebook AI Research (FAIR), Tsinghua University, and Cornell University. A portion of the ImageNet database, which has over a million photos, is used to pretreat DenseNet-201. The network has an image input size of 224 × 224.

3.4.3 Training and Testing Conditions: All four models were trained and tested in the same way to provide an equitable comparison. The dataset was divided into training, validation, and testing sets, and all models used the same parameters, such as batch size, learning rate, and number of epochs. To improve generalization and training efficiency, data augmentation was used consistently.

3.5 Training Methodology: The training process for the deep learning models was designed to be consistent across all experiments to ensure a fair comparison of their performance. For factors like batch size, learning rate, number of epochs, and data splits, this required using the same setups. Because these settings were consistent, it was possible to get accurate information about the relative advantages and disadvantages of each model. A batch size was carefully chosen to strike a balance between the memory constraints of the hardware and the efficiency of training. Larger batch sizes can speed up training but may lead to memory issues, while smaller batch sizes improve generalization but increase computational time. Based on preliminary experiments, an optimal batch size was selected to facilitate smooth training without overloading the system. The models were trained for 100 epochs, with a duration determined through initial tests to ensure adequate learning while avoiding over-fitting. During the early experiments, it was observed that most models converged and stabilized within this epoch range, making it an ideal choice for efficient training. To optimize the learning process, the Adam optimizer was employed. This optimizer combines the benefits of both momentum and adaptive learning rate techniques, which makes it particularly effective for deep learning tasks. The adaptive learning rates allow the model to adjust the step size for parameter updates dynamically, ensuring faster convergence. The momentum component helps the optimizer avoid getting stuck in local minima, making the learning process more robust. Adam has been widely recognized as a reliable optimizer for tasks involving limited data, as it balances exploration and exploitation during training. For the binary classification job of differentiating between brain pictures with and without tumors, binary cross-entropy was the loss function that was employed. This loss function penalizes inaccurate predictions more severely by calculating the discrepancy between the actual labels and the anticipated probabilities. The models were adjusted to produce precise classifications by reducing this loss. 3.6 Performance Matrix To assess the effectiveness of the trained models, a comprehensive set of performance matrix was used. These matrices provided insights into various aspects of the models' classification capabilities and helped identify areas for potential improvement:

3.6 Evaluation Metrix:

The performance of the model was assessed using the following matrix:

3.6.1 Accuracy: Accuracy measured the proportion of correctly classified samples to the total number of samples. It provided an overall measure of how well the model performed across the entire dataset. However, accuracy alone could be misleading in imbalanced datasets, as it does not account for the distribution of classes.

3.6.2. Precision: Precision measured how well the model predicted cases of tumors. The ratio of true positive predictions to all positive predictions (false positives and genuine positives) was its definition. High precision showed that the model successfully reduced false positives, which is essential for medical diagnostics in order to cut down on needless alerts.

3.6.3. Recall: Recall assessed the model's capacity to recognize every real instance of a tumor. It was determined by dividing the total number of true positive cases (including true positives and false negatives) by the number of true positive forecasts. By ensuring that the model recorded the majority of tumorous occurrences, high recall decreased the possibility of missing important diagnoses.

3.6.4. F1-Score: Precision and recall were merged into a balanced metrix by the F1 score. It was calculated by taking the harmonic mean of recall and precision, giving each equal weight. Because it provided a single value that represented the trade-off between precision and recall, the F1 score was especially helpful for assessing models on imbalanced datasets.

3.6.5. Confusion Matrix: To give a thorough analysis of the model's pre dictions, confusion matrices were created. The following counts were shown in the matrix: True Positives (TP): Correctly predicted tumorous cases. True Negatives (TN): Correctly predicted non-tumorous cases. False Positives (FP): Non-tumorous cases incorrectly classified as tumorous and False Negatives (FN): Tumorous cases missed by the model.

This detailed analysis helped pinpoint specific areas where the model might need improvement, such as reducing false negatives to ensure no tumorous cases were overlooked.

3.7 Importance of Consistency and Evaluation: By maintaining consistency in training configurations and employing a diverse set of performance matrices, this study ensured that the models were rigorously evaluated. The combination of accuracy, precision, recall, and F1 score offered a holistic view of the models' capabilities, while confusion matrices provided granular insights into their performance. Together, these approaches formed a robust framework for assessing and comparing the deep learning models, ultimately guiding the selection of the most reliable model for brain MRI classification.

4. PROPOSED ALGORITHMS:

4.1 Introduction: Convolutional Neural Network (CNN) is a unique class of deep learning neu ral networks which is customized for handling the computer vision related tasks. As this approach utilizing the phenomenon of convolution of neuron unlike standard neural networks, it is able to perform variety of unique applications such as image segmentation, object detection, image processing. It is playing a pivot role in many engineering and general applications in particular in tracing the specific abnormal features in medical image processing. This unique feature of tracing abnormal parameters from the given image and categorize that image into a specified class made use of these CNN in justifying the presence of tumors, tissues from the trained data.

4.1.1 Role of CNN in image processing:

The CNN process the data by discretization the given image into grid like structure known as kernel. These kernels are able to extract the visual features and compare those features with the new images given for the analysis. However it need rigorous trying to identify the similar visual features from the image. This makes the CNN as an exceptional approach in image pro cessing and recognition. There are many layers to extract these features, broadly they are convolutional and pooling layers. These layers are the heart of CNN architecture. The convolutional layers would able to extract local features of image by applying filters viz texture, size, edges, and other visual parameters. Whereas the pooling layers are supporting to resize the spatial dimensions extracted from convolutional layers. This resizing helps to lower the model complexity without losing the crucial features.

4.2 VGG-16: It is architected by Visual Geometry Group (VGG) was coined by Karen et al. with 16 convolutional and pooling layers. They structured this model to to extract the features and analyze them from the visual data by applying deep CNN. This VGG model is able to investigate the deepness of layers with a diminutive convolutional filter size of 3 × 3 even to analyze the large images. VGG-16 is composed of 13X3 convolutional and fully connected layers with 5 max-pooling layers. The architecture consists of several blocks with 64 filters in first block and this number is increased to 512 with a step size of 2 multiplication factor. The last three layers are fully connected in which first two are hidden layers with 4096 neurons while the last layer is output layer with 1000 neurons.

4.3 VGG-19: It is development of previous model with more advanced features to extract the fine tuned image parameters. It is more popular by its healthy feature extraction potential than the earlier version. This pre-trained model is more efficient in image analysis, object detection, image processing and style transfer. VGG-19 is also a kind of deep CNN with 19 weight layers, comprising 16X3 convolutional and fully connected layers. It is more efficient to accurately predict and extract the features and it is easier to understand and implement. The pivotal layers of VGG-19 architecture are: The convolutional layers are designed with a very small sized filter of 3X3 with a stride and padding of each 1 to have high spatial resolution. It is interconnected with a rectified linear unit to accept and handle the non linearity. Nevertheless it is also connected with the pooling layers of 2X2 filter to control the spatial dimensions. As similar to the earlier version 3 fully connected layers are existing at the end of convolutional layers, however this architecture also facilitates with softmax layer for final output with class of probabilities.

4.4 Inception-V3: Inception-V3 is a CNN architecture introduced by Google researchers as an improvement over its predecessors, Inception-V1 (GoogLeNet) and Inception V2. It is widely used for image classification and feature extraction tasks in computer vision. Inception architectures aim to optimize the computational cost of deep CNNs while maintaining high accuracy. They utilize Inception modules, which perform multi-scale processing by applying different convolution filters and concatenating the outputs, allowing the network to efficiently capture spatial hierarchies and patterns.

4.5 ResNet-50 (Residual Networks): The ResNet architecture is considered to be among the most popular Convolutional Neural Network architectures around. Introduced by Microsoft Research in 2015. ResNet-50 is widely used for image classification, object detection, and transfer learning due to its efficiency and performance on large datasets like ImageNet. ResNet-50 has 50 layers, making it a deep network while still trainable due to the residual connections. It includes 48 convolutional layers, 1 fully connected (FC) layer, and 1 max-pooling and average-pooling layer each

4.6 DenseNet-201: The study ”Densely Connected Convolutional Networks” by Gao Huang et al., published in the year 2017, introduces DenseNet, short for Dense Convolutional Network, a deep learning architecture for CNNs. By introducing novel connectivity architecture within CNNs and tackling issues like feature reuse, vanishing gradients, and parameter efficiency, DenseNet transformed the field of computer vision. DenseNet creates direct connections between every layer in a block, in contrast to conventional CNN designs where each layer is only connected to layers that come after it. By allowing feature maps from all previous layers to be received as inputs by each layer, this deep connectedness promotes substantial information flow across the net work. Convolutional, pooling, and fully linked layers are among the 201 layers that make up DenseNet-201.

5. RESULTS AND DISCUSSION:

5.1 Detailed Procedure: In the current study, we created a completely automated brain tumor classification system. The initial steps involved preprocessing the raw MRI pictures, cropping them, and mechanically identifying the boundaries of the brain tissue. The detailed procedure is presented in fig 5.1

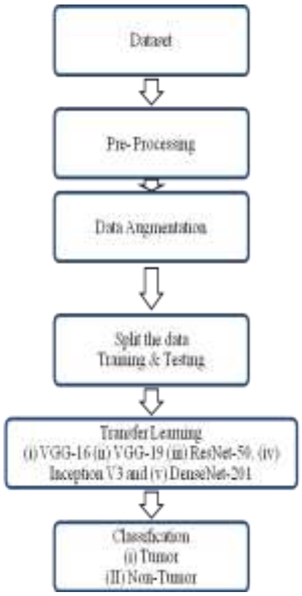
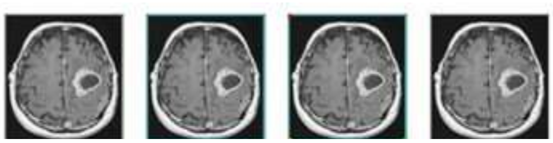


Fig 5.1 Proposed methodology

A data-augmentation technique was then used to expand the dataset. The transfer learning approach lowered the processing load and produced successful outcomes with minimal data.

5.2 Dataset and Preprocessing:

The dataset used in this study consisted of 253 brain MRI scans in total, which Chakrabarty collected and made publicly available. Out of these pictures, 155 had tumors and 98 did not.. Twenty percent of the entire dataset is utilized for testing, while eighty percent is used for training.



(i) Original Image (ii) identify the bigger contours
(iii) find extreme points (iv) crop the image

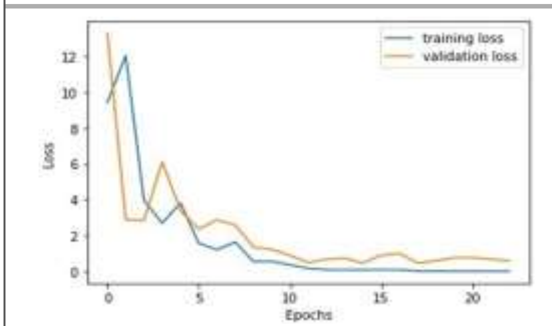
5.3 Preprocessing of the Dataset:

For all the images, the borders and polar points (i.e., the four endpoints: right, left, top, and bottom) were identified and tuned during the preprocessing stage. The other exterior parts were eliminated within the code. The entire dataset was resized to 224 × 224 pixels by cropping along the length and width of the image data.

5.4 CNN Implementation

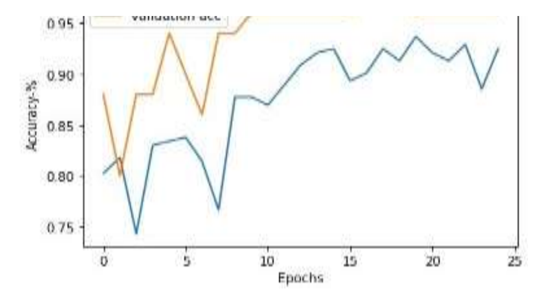
The VGG-16 model was employed as the first convolutional neural network (CNN). The model was initialized with ImageNet weights, and a dense layer with a sigmoid activation was added for binary classification. The accuracy achieved was 99.01% with a loss of 1.19.

Training and Validation Accuracy Curves for VGG-16 Model



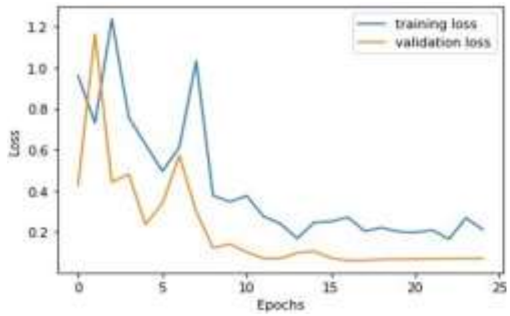
Training and Validation Loss Curves for VGG-16 Model

The VGG-19 model is similar to VGG-16, but it has three additional convolutional layers. The accuracy



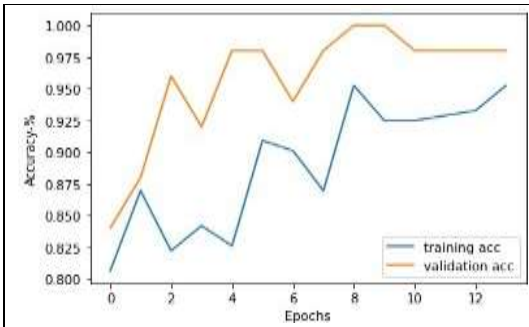
Training and Validation Accuracy Curves for

VGG-19 Model

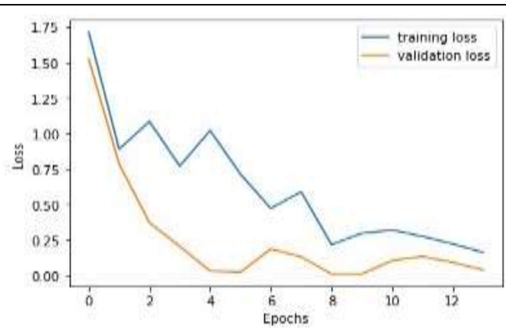


Training and Validation Loss Curves for VGG-19 Model

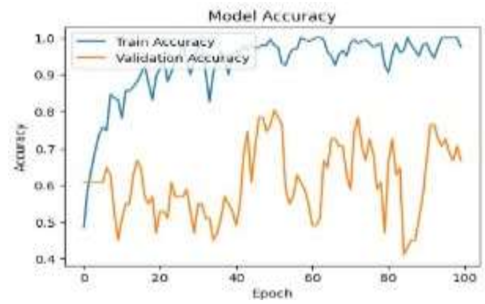
The Inception-V3 model was implemented and trained using early stop ping and checkpoint callbacks. The model achieved an accuracy of 98.52% with a loss of 3.13



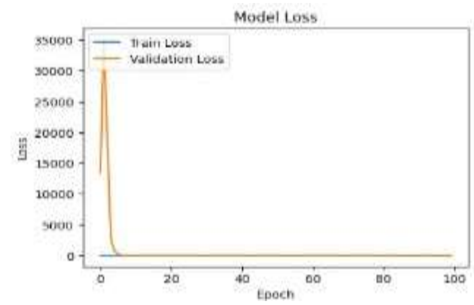
Training and Validation Accuracy Curves for Inception V3 Model



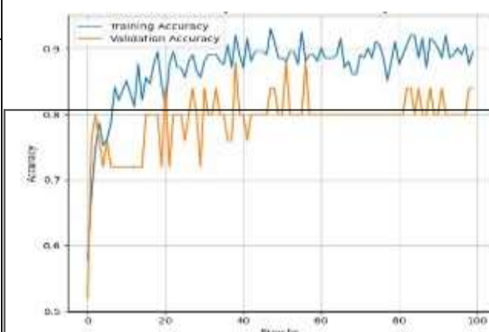
Training and Validation Loss Curves for Inception V3 Model



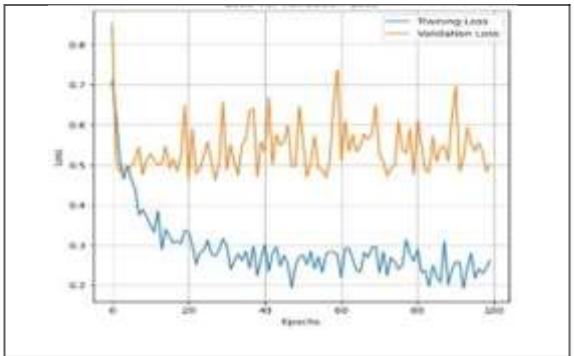
Training and Validation Accuracy Curves for ResNet50 Model



Training and Validation Loss Curves for ResNet50 Model



Training and Validation Accuracy Curves for DenseNet201 Model



Training and Validation Loss Curves for DenseNet201 Model

Comparison of various models: ResNet-50 achieves the highest accuracy (99.88%), indicating its superior ability to correctly classify samples overall. DenseNet-201, while still performing well, exhibits comparatively lower metrics in all categories, which might indicate challenges in optimizing for the given dataset or application. Comparison performance of various models are presented in Table.5.1.

Table 5.1: Performance comparison of various models

Model	Accuracy	Recall	Precision	F1 Score
VGG 16	99.01	98.18	99.88	99.08
VGG19	99.51	98.73	99.98	99.17
ResNet50	99.88	98.75	98.77	99.24
Inception V3	99.51	93.25	93.84	98.63
DenseNet 201	95.90	93.70	92.75	91.21

6. CONCLUSIONS:

Brain tumors, being critical and life-threatening medical conditions, require early and precise diagnosis to ensure effective treatment planning. Traditional manual methods for analyzing MRI data are time-consuming and prone to subjective biases, highlighting the necessity of automated approaches. The methodologies implemented in this study involved leveraging pre-trained deep learning models and fine-tuning them for brain tumor classification. The dataset was rigorously preprocessed using normalization, augmentation, and segmentation techniques to enhance feature extraction capabilities. The research presented in the current study investigates on the application of transfer learning using state-of-the-art deep learning architectures, such as VGG-16, VGG-19, ResNet-50, Inception-V3, and DenseNet-201, for the accurate and efficient detection of brain tumors from MRI images. The models were evaluated based on metrics such as accuracy, precision, recall, and F1-score to assess their effectiveness comprehensively. Amid all models, ResNet-50 exhibited superior performance of 99.88 % due to its deep architecture and efficient feature extraction, while VGG-19 and Inception-V3 followed closely demonstrating robust capabilities for tumor classification. By analyzing the strengths and limitations of these architectures, the study provides valuable insights into their suitability for clinical applications, paving the way for improved diagnostic accuracy and efficiency.

REFERENCES:

[1]. H. Abbasi, M. Orouskhani, S. Asgari, and S. S. Zadeh. Automatic brain ischemic stroke segmentation with deep learning: A review. Neuro science Informatics, 3(4):100145, 2023.

[2]. A. B. Abdusalomov, M. Mukhiddinov, and T. K. Whangbo. Brain tumor detection based on deep learning approaches and magnetic resonance imaging. Cancers, 15(16):4172, 2023.

[3]. N. Abiwinanda, M. Hanif, S. T. Hesaputra, A. Handayani, and T. R. Mengko. Brain tumor classification using convolutional neural net work. In World Congress on Medical Physics and Biomedical Engi neering 2018, pages 183–189. Springer, 2019.

[4]. N. Abuared, A. Panthakkan, M. Al-Saad, S. A. Amin, and W. Mansoor. Skin cancer classification model based on vgg 19 and transfer learning. In 2020 3rd International Conference on Signal Processing and Information Security (ICSPIS). IEEE, 2020.

[5]. P. Afshar, A. Mohammadi, and K. N. Plataniotis. Brain tumor type classification via capsule networks. In 2018 25th IEEE International Conference on Image Processing (ICIP), pages 3129–3133, 2018.

[6]. Sanjay A. Agarwal. Advancements in nsfw content detection: A com prehensive review of resnet-50 based approaches. International Journal of Systems and Applications in Engineering, 2023

[7]. M. Agn, P. M. af Rosensch¨ old, O. Puonti, M. J. Lundemann, L. Mancini, and A. Papadaki. A modality-adaptive method for segmenting brain tumors and organs-at-risk in radiation therapy planning. Medical Image Analysis, 54:220–237, 2019.

[8]. S. Ahmad and P. K. Choudhury. On the performance of deep transfer learning

networks for brain tumor detection using mr images. IEEE Access, 10(Ml):59099–59114, 2022.

[9]. A. A. Akinyelu, F. Zaccagna, J. T. Grist, M. Castelli, and L. Rundo. Brain tumor diagnosis using machine learning, convolutional neural net works, capsule neural networks and vision transformers, applied to mri: A survey. Journal of Imaging, 8(8):1–40, 2022.

[10]. Bhagwat, V. B. (2024). A simplified transition from EBS Payroll to Cloud Payroll: Benefits and Drawbacks. Journal of Computational Analysis and Applications, 33(6).

[11]. J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak. Brain tumor detection and classification using machine learning: a compre hensive survey. Complex Intelligent Systems, 8(4):3161–3183, 2022.

[12]. Javaria Amin et al. Brain tumor detection and classification using ma chine learning: A comprehensive survey. Complex Intelligent Systems, 8(4):3161–3183, 2022.

[13]. S. Bauer, R. Wiest, L. P. Nolte, and M. Reyes. A survey of mri-based medical image analysis for brain tumor studies. Physics in Medicine and Biology, 58:R97, 2013.

[14]. Reddy, S. K. R. Developing a Modular AI Framework to Enhance Scalability and Personalization in Next-Generation Reward Platforms.

[15]. M. N. Islam, M. S. Azam, M. S. Islam, M. H. Kanchan, A. H. M. S. Parvez, and M. M. Islam. An improved deep learning-based hybrid model with ensemble techniques for brain tumor detection from mri image. Informatics in Medicine Unlocked, 47, 2024.

[16]. Md. Naim Islam, Md. Shafiul Azam, Md. Samiul Islam, Muntasir Hasan Kanchan, A.H.M. Shahariar Parvez, and Md. Monirul Islam. An im proved deep learning-based hybrid model with ensemble techniques for brain tumor detection from mri images. Available online 3 April 2024, 2024.

[17]. K. Kanchana, S. Kavitha, K. J. Anoop, and B. Chinthamani. Enhancing skin cancer classification using efficient net b0-b7 through convolutional neural networks and transfer learning with patient-specific data. Asian Pacific Journal of Cancer Prevention, 25(5):1795–1802, 2024.

[18]. Henry Cyril. (2025). AI-DRIVEN ANOMALY DETECTION, OUTAGE PREDICTION, AND SELF-HEALING IN TELECOM PROVISIONING SYSTEMS. International Journal of Applied Mathematics, 38(12s), 2817–2832. https://doi.org/10.12732/ijam.v38i12s.1589.

[19]. S. Krishnapriya and Y. Karuna. Pre-trained deep learning models for brain mri image classification. Frontiers in Human Neuroscience, 17, 2023.

[20]. G. Pouliquen et al. Deep learning-based noise reduction preserves quan titative mri biomarkers in patients with brain tumors. Journal of Neu roradiology, 51(4):1–7, 2024.

[21]. Prodduturi, S. M. K. (2024). Investigating the challenges and opportunities of cybersecurity in the era of remote work. European Journal of Advances in Engineering and Technology, 11(10), 80-84.

[22]. Reddy, S. K. R. (2021). Strengthening the Security of Loyalty Reward Systems: An In-Depth Analysis of Emerging Cyber Threats and Protection Mechanisms. Journal of Computational Analysis and Applications, 29(6).

[23]. A. Kumar Sahoo, P. Parida, K. Muralibabu, and S. Dash. Efficient simultaneous segmentation and classification of brain tumors from mri scans using deep learning. Biocybernetics and Biomedical Engineering, 43(3):616–633, 2023.

[24]. P. S. Smitha, G. Balaarunesh, C. Sruthi Nath, and A. Sabatini S. Classi f ication of brain tumor using deep learning at early stage. Measurement Sensors, 35(July):101295, 2024.

[25]. M. Soui and Z. Haddad. Deep learning-based model using densenet201 for mobile user interface evaluation. International Journal of Hu man–Computer Interaction, 2023.

[26]. Kavita A. Sultanpure, Jayashri Bagade, Sunil L. Bangare, Manoj L. Bangare, Kalyan D. Bamane, and Abhijit J. Patankar. Internet of things and deep learning based digital twins for diagnosis of brain tumor by analyzing mri images. Available online 20 May 2024, 2024.

[27]. S. Tabatabaei, K. Rezaee, and M. Zhu. Attention transformer mech anism and fusion-based deep learning architecture for mri brain tu mor classification system. Biomedical Signal Processing and Control, 86(PA):105119, 2023.

[28]. Sadafossadat Tabatabaei, Khosro Rezaee, and Min Zhu. Attention transformer mechanism and fusion-based deep learning architecture for mri brain tumor classification. Biomed Signal Process Control, 86, 2023.

[29]. P. Wang and A. C. S. Chung. Relax and focus on brain tumor segmen tation. Medical Image Analysis, 75:102259, 2022.