J. Integr. Sci. Technol. 2024, 12(4), 785

Journal of Integrated
SCIENCE & TECHNOLOGY

Frequent CNN based ensembling for MRI classification for Abnormal Brain Growth detection

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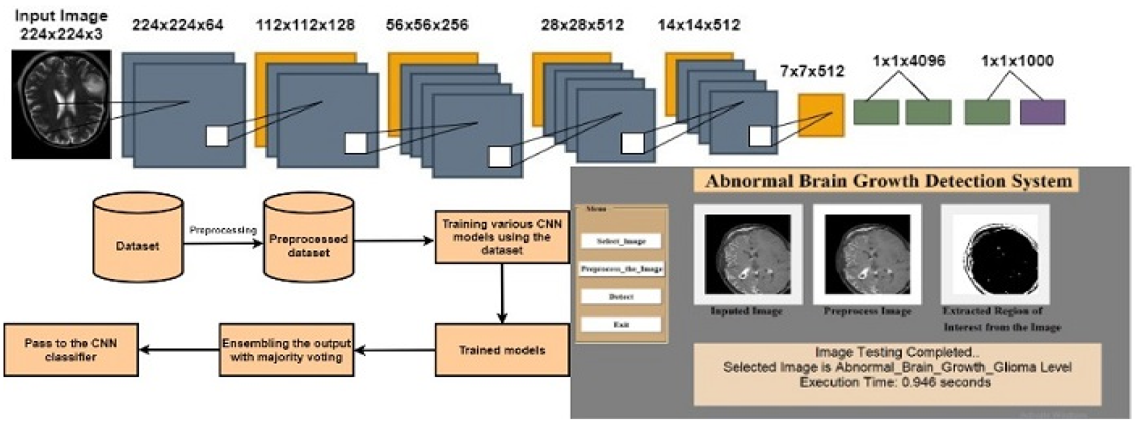
Received on: 10-Dec-2023, Accepted 25-Dec-2023 and published on: 27-Dec-2023

Article

ABSTRACT



Digital image processing is a key player in the analysis of medical images, particularly in understanding the intricacies of abnormal brain growth development. Notably, the application of CNN algorithms to MRI images accelerates abnormal brain growth detection with enhanced accuracy; facilitating prompt decision-making by radiologists. This research focuses on finding abnormal brain growth using advanced CNN computer techniques. The study is split into three main steps. In the first step, brain MRI images are pre-processed by applying selected pre-processing techniques. In the second step, machine learning feature extraction methods are applied to pick out important features from these images. Finally, CNN models such as VGG, ResNet, DenseNet, and MobileNet are applied to classify the MRI images at a detailed level. The ensemble is done to improve the accuracy of the classification of MRI images. The results from study indicate easy automated abnormal brain growth detection that save radiologists' time and improve the efficiency of early diagnosis.

Keywords: Abnormal Brain Growth, Digital Pathology, CNN, VGG19, ResNet, DenseNet, MobileNet

INTRODUCTION

The human body comprises various cell types, each with a specific function, growing and dividing in an orderly manner to maintain overall health. However, when certain cells lose control over their growth, they form a mass known as a abnormal brain growth. abnormal brain growth result from abnormal cell development, and they can be benign or malignant. Malignant tumors lead to cancer, while benign tumors are non-cancerous.[1] Abnormal brain growth originate from uncontrolled cell proliferation, affecting brain cells, membranes, glands, or nerves. They may weaken brain cells and exert pressure inside the skull, posing a challenge in medical diagnosis. Medical imaging data from devices like X-rays and CT scans are crucial for accurate diagnosis.[2] Abnormal brain growth diagnosis is challenging due to the diverse characteristics of abnormal cells in brain, such as shape, size, and location. Early detection is difficult, but once identified, appropriate treatments like chemotherapy, radiotherapy, and surgery can be initiated. Medical imaging technology, including CT scanners, Ultrasound, and Magnetic Resonance Imaging, revolutionized diagnosis and enabled minimally invasive surgeries. Digital image processing techniques enhance data interpretation for physicians.[3] Abnormal brain growth are categorized as primary or secondary, with primary abnormal brain growth originating in the brain. They are further classified as benign or malignant, each requiring specific treatment approaches. Malignant abnormal brain growth are more serious, potentially spreading to nearby healthy tissue. Convolutional Neural Network (CNN) frameworks aid in

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Cite as: *J. Integr. Sci. Technol., 2024, 12(4), 785. URN:NBN:sciencein.jist.2024.v12.785*

segmentation-free feature extraction, contributing to abnormal brain growth detection. Detecting abnormal brain growth is challenging due to variations in location, type, size, and shape. Early identification is crucial for treatment decisions and improved chances of survival. Machine learning techniques, specifically CNN-based, classify brain images as normal or abnormal, facilitating tumor extraction. The CNN model incorporates convolutional, max-pooling, flatten and fully connected layers. Current research focuses on the detection and classification of abnormal brain growth using advanced image processing and computer vision applications. Machine learning has proven effective feature extraction in biomedical fields, particularly in abnormal brain growth preprocessing through image analysis and detection through CNN models. This research aims to critically analyze existing findings to enhance the understanding of abnormal brain growth detection and classification using CNN models techniques are applied to brain MRI images.

Magnetic resonance imaging is a pivotal tool in abnormal brain growth detection and utilizes techniques like T1-weighted, T2-weighted, and contrast-enhanced imaging. This approach involves a three-stage process. Initially, examine the diversity of coarse regions in the MRI image. Extract shape and texture features from tiled regions, reduce the dimensionality of these features, and cluster them to create representative groups. In the second stage, it conducts a detailed analysis of a single representative tile from each group. Using CNN classifier, it generates a diagnostic decision value for each tile. A weighted voting scheme combines these decision values to provide a diagnosis for the entire image. This method aims to make the analysis more efficient and accurate. Strategically analyze coarse regions, extracting essential features such as shape and texture from tiled sections. In essence, approach offers a nuanced and efficient solution to the complexities posed by large pathology images, ensuring that the computerized analysis is not only accurate but also focused on the relevant information critical for diagnosis and research advancements.

LITERATURE SURVEY

In the research paper by Ramdas Vankdothu, et.al.[4] explained these scans are commonly employed in diagnosing various conditions like head traumas, malignancies, and skull injury. Primary focus was on enhancing the efficiency and simplifying the complexity associated with the segmentation process of CT-based images. By investigating and refining the segmentation techniques specific to CT scans, aim to contribute to a more streamlined and effective approach to identifying and delineating abnormal brain growth in these diagnostic images. This research holds promise for improving the overall diagnostic process for conditions affecting the brain, offering potential benefits in terms of accuracy and speed. Yi-Xin Huang, et.al.[5] suggested CNN-based deep learning model for sorting many forms of abnormal brain growth, where the design has an ordering accuracy for the group of abnormal brain growth types. Hossain[6] contributed to the collective understanding of automated abnormal brain growth detection, offering valuable insights to researchers, practitioners, and stakeholders in the medical and machine learning communities. This type of study is crucial for staying abreast of the latest developments in the field, guiding future research directions, and ultimately advancing the capabilities of automated abnormal brain growth detection systems. Ashwini S Shinde, et.al.[7] evaluated several cutting-edge Machine Learning techniques designed for tumor classification, distinguishing between benign and malignant cases. The investigated methods encompass a diverse array of approaches, including Logistic Regression, Multilayer Perceptron, Decision Trees, Naive Bayes classifier, and Support Vector Machines. The aim is to comprehensively analyse the effectiveness and performance of each technique in the critical task of abnormal brain growth classification. By delving into these state-of-the-art methodologies, seek to discern their respective strengths and limitations, providing valuable insights into their applicability and potential contributions to enhancing the accuracy and reliability of tumor diagnosis. Omer Turk et.al.[8] developed an automated system for detecting abnormal brain growth using advanced deep learning models, namely ResNet50, InceptionV3, and Mobile Net focusing on analyzing brain images, a crucial diagnostic tool. Additionally, we're incorporating Class Activation Maps (CAMs) indicators to enhance the interpretability of the models. By doing this, aim to create a more accurate and reliable method for identifying abnormal brain growth through the combination of these powerful deep-learning architectures and meaningful visualizations provided by CAMs. This approach could potentially improve the efficiency and precision of abnormal brain growth diagnosis using MRI scans.

Parvin Razzaghi, et.al.[9] described the challenge of brain image segmentation, the concept of knowledge transfer, both between and within different modalities. A key aspect of this transfer is domain adaptation, which plays a crucial role in overcoming the issue of disparate distributions between the sets used for training and testing. Arkapravo Chattopadhyay, et.al.[10] improved the accuracy of detecting and categorizing abnormal brain growth in MRI images by combining the strengths of both advanced neural networks and established classification techniques. This approach could lead to more precise and reliable results in identifying and understanding brain abnormalities from medical images. K.S. Ananda Kumar et al[11] informed in simple terms, using a sophisticated neural network that has been pre-trained on a large dataset (inspired by nature) to quickly and accurately identify and categorize brain images. This approach combines the strengths of deep learning and transfer learning, aiming to improve the efficiency and accuracy of detecting various features in brain images for better classification.

Detecting abnormal brain growth poses challenges due to the diverse nature of tumor tissues among different patients, often resembling normal tissues, making the task complex. The primary objective of current study is to accurately classify the presence of a abnormal brain growth or a healthy brain, enabling early-stage detection.[12] This methodology enhances the speed and precision of abnormal brain growth detection, providing automation in image processing and analysis, thereby improving the identification of brain structures in the realm of medical science. The focus extends to abnormal brain growth Segmentation, a critical medical image analysis task involving the separation of abnormal brain growth from normal brain tissue in imaging scans.[13] Leveraging convolutional neural networks (CNN) proves advantageous, as they autonomously learn intricate features from multi-modal brain images, enhancing accuracy. This approach not only automates image processing but also contributes to the refined identification of both healthy and abnormal brain growth tissues. Recognizing the pivotal role of early-stage abnormal brain growth detection in increasing patient recovery chances after treatment, the study emphasizes the importance of image processing. The fundamental objective is to convert images into a digital format, enabling specific operations for obtaining models or extracting pertinent information from the images.[14] The main goal is to significantly reduce the fatality rate associated with abnormal brain growth, underscoring the importance of early identification. The study aims to streamline the detection and classification of abnormal brain growth, particularly through the development of a segmentation and detection method utilizing MRI sequence images. This method serves as a valuable tool for identifying abnormal brain growth areas, contributing to the broader effort to improve outcomes in abnormal brain growth diagnosis and treatment.[15]

METHODOLOGY

According to the literature review, automated detection of abnormal brain growth is imperative, particularly when human lives are at stake, demanding high accuracy. The automated process involves the extraction of features and classification CNN algorithms.[16] This paper introduces a system designed for the automatic detection of abnormal brain growth in MRI images. The application of various imaging techniques serves the ultimate purpose of extracting crucial information from the given MRI images. While the classification of abnormal brain growth is a vital yet time-intensive task performed by medical experts, the digital image processing community has made significant strides, developing numerous machine learning algorithms and CNN models.[17] Extensive research has explored abnormal brain growth detection using image processing and soft computing techniques, each with its distinct advantages. The paper delves into the methods and algorithms employed in the proposed approach for the classification of brain MRI images. In Fig.1 it is shown the how data is pre-processed for training the various CNN models to make a trained classification model for abnormal brain growth detection. It shows rough idea about structure of the MRI abnormal brain growth detection and classification.[18]

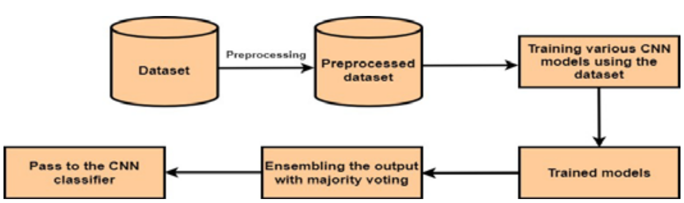

Figure 1. General system architecture

In Figure 2 detailed system architecture of abnormal brain growth detection and classification is shown. In first step MRI image to, train the classification algorithm using the MRI brain dataset. The accuracy of the learned model is calculated and it is evaluated. The various CNN models such as VGG, ResNet, DenseNet and MobileNet to make the best classification model for the detection of abnormal brain growth and gives brain images of patients as input to the classification model at the last ensemble the classification output for majority voting to detect the abnormal brain growth.[19]

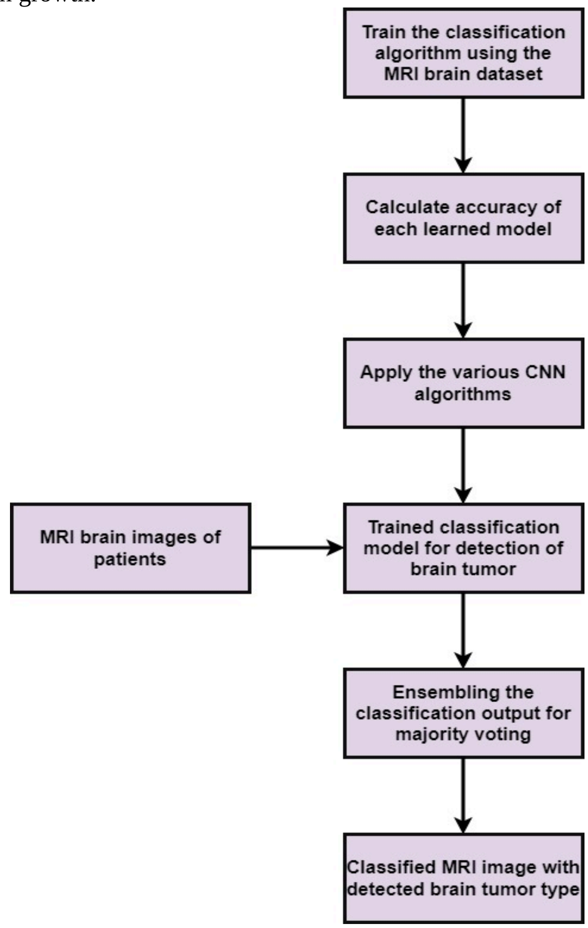

Figure 2. Detailed System Architecture

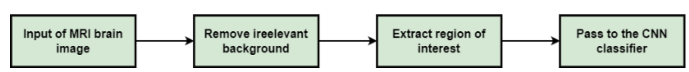

Figure 3. MRI Image Data processing

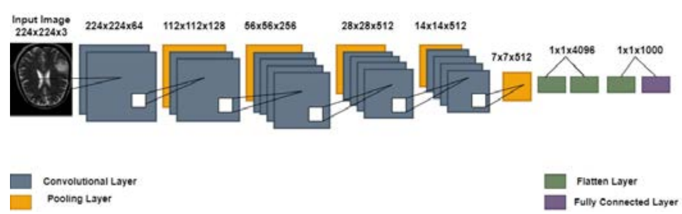

Figure 4. CNN Layer Processing

The dataset includes 1320 images of human brain MRI. These images are classified into three types: glioma, meningioma, and pituitary. 330 images of glioma abnormal brain growth, raises to cancer that disturbs the brain, cranial nerves, or other portions of the nervous system. 330 images of pituitary abnormal brain growth, Pituitary abnormal brain growth.[20]

It initiate in the pituitary gland, which is found inside the skull but is not part of the brain.330 images of meningioma brain tumors, On the other hand, meningioma tumors develop from the meninges, the membrane that shields the brain and spinal cord. They are the most common primary brain tumors in adults. And the other 330 are normal brains.[21]

To enhance accuracy, preprocessing steps are undertaken to eliminate artifacts present in these images. In Fig.3 the processing time is optimized by excluding unnecessary information from the image background, such as the skull, background and scalp, leaving only the region of interest. The Brain Surface Extractor employed to effectively remove the brain and skull. Preprocessing proves essential as it not only eliminates unwanted elements but also improves the overall image data, enhancing crucial features necessary for subsequent processing steps.[22]

A VGG19 (Visual Geometry Group 19) Convolutional Neural Network (CNN) architecture is a type of deep neural network it consists of 19 layers that employs various convolutional layers to sift through inputs and extract useful information. Convolutional filters are applied to the input data in these layers, calculating the output of neurons linked to specific regions in the input. Fig.4 the CNN model consists of four key layers: a convolutional layer, a pooling layer, flatten layer and a fully connected layer. The convolutional layer involves essential parameters like stride, padding, and filter size. Multiple filters are utilized in each layer to extract detailed features. The filters move across the images based on a specified stride, where a stride size of one or two is typically employed; exceeding this value can negatively impact CNN performance.[23] Each convolutional layer is designed to carry out a specific task in the overall process. The number of filters increases deeper into the network, providing a hierarchical feature representation. Pooling layer helps reduce the spatial dimensions of the feature maps, leading to a more compact representation and capturing the most important features, it preserves important information extracted by the convolutional layers. Flatten layer connecting the spatial information captured by to the densely connected layers that make classification decisions. Fully connected layer uses softmax activation to produce probability scores for different classes. These scores in the presence of each class in the input image. After completing all layers it classifies whether the abnormal brain growth has occur or not.[24]

RESULTS AND DISCUSSION

The study conducted focused on analysing brain images through a process that involved extracting texture-based features. These features serve as distinctive characteristics derived from the patterns and textures within the images. The utilization of a specialized model was inherent to the following classification task.[25] This model, trained on the abstract texture features, played a pivotal role in categorizing and distinguishing different aspects or conditions within the brain images. By grasping advanced techniques for feature extraction and employing a tailored classification model, the research aimed to enhance understanding of the intricate details present in the brain images, contributing to more accurate and fine classifications for various neurological conditions or characteristics.[26] This approach emphasizes the importance of combining advanced imaging analysis with advanced computational models to glean meaningful insights from complex datasets.[27]

Algorithm: CNN Classification for Abnormal Brain Growth Detection

Input: Brain Image

Output: Classified abnormal brain growth Label

Use the MRI image dataset for model training

Train the model using convolutional neural network (VGG, ResNet, DenseNet, and MobileNet)

Using cross validation score calculate the accuracy of various models

Input the test image 100X100 pixels.

Use trained model to predict the class label of abnormal brain growth

Make a list of predicted class labels for various trained models

By ensembling find the final class label of the abnormal brain growth by majority voting

The F1 score is calculated using precision and recall. It combines precision and recall into a single value; it is used for uneven class distribution. Precision is the ratio of true positives. Precision focuses on the accuracy of positive predictions. It works on True Positive (TP), false Positive (FP) and False Negative (FN).[28]

Table1. Classification Report of CNN Algorithm

Class	Precision	Recall	F1_score	Support
Normal Brain	0.83	0.91	0.87	390
Glioma abnormal brain growth	0.88	0.83	0.87	460
Meningioma abnormal brain growth	0.91	0.86	0.90	460
Pituitary abnormal brain growth	0.93	0.88	0.92	370
Accuracy	0.90	560	-	-
Macro avg	0.87	0.91	0.88	560
Weighted avg	0.89	0.90	0.90	560

$$\text{F1\_score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad \text{.......................... (1)}$$

It combines two important performance measures: precision and recall. Precision represents the accuracy of positive predictions, while recall (or sensitivity) measures the ability of the model to capture all the relevant instances.

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{.. (2)}$$

Precision is the number of true positives divided by the sum of true positives and false positives. It is a measure of the accuracy of positive predictions.

$$\text{Recall} = \frac{TP}{TP+FN} \quad \text{...(3)}$$

Recall is the number of true positives divided by the sum of true positives and false negatives. It is a measure of the model's ability to capture all the relevant instances.

Table 2. Classification Models with Cross Validation Score

Model	CV score K=1	CV score K=2	CV score K=3	CV score K=4
VGG	0.95	0.92	0.91	0.95
ResNet	0.90	0.90	0.90	0.90
DenseNet	0.89	0.90	0.91	0.92
MobileNet	0.87	0.88	0.86	0.86

The initial step involves providing the system with a brain MRI image, which could be either a representation of a normal brain or one depicting the presence of a abnormal brain growth. This input image undergoes a processing phase where the system analyzes and extracts relevant features. The processing stage is key as it lays the foundation for following steps in the algorithm. This initial processing step serves as the threshold, enabling the system to discern key patterns and characteristics within the brain image, setting the stage for further examination and classification.[29]

In the processing phase, the brain image undergoes an important step known as grey feature extraction. This method systematically processes the entire dataset, focusing on isolating and removing the background portion of the brain. The goal is to generate a specific section of the brain that holds diverse features for analysis. By sharpening this particular region, the system enhances its ability to identify subtle abnormalities, such as the presence of a abnormal brain growth. This targeted approach facilitates a more efficient and accurate determination of whether a abnormal brain growth is present in the examined image or if the brain is in a normal state. The implementation of grey feature extraction thus simplifies the identification process, contributing to a more precise assessment of brain health.[30]

Utilizing Convolutional Neural Network (CNN) prediction, the testing phase is necessary to determine whether a given brain image corresponds to a normal state. Following the processing steps, the CNN model, trained to recognize patterns and features indicative of normal brain structures, is applied to the tested image. Through this predictive analysis, the system can effectively discern whether the features extracted align with those typical of a healthy brain. This final step in the process serves as a determinative assessment, providing a clear identification of whether the examined brain image is indicative of a normal state or if deviations warrant further attention. The use of CNN prediction improves the accuracy and reliability of the system in classifying brain images and contributes to the overall effectiveness of the diagnostic approach.[31]

In Figure 5 result of glioma abnormal brain growth detected. High-grade gliomas represent a form of malignant, or cancerous, abnormal brain growth characterized by their rapid growth and

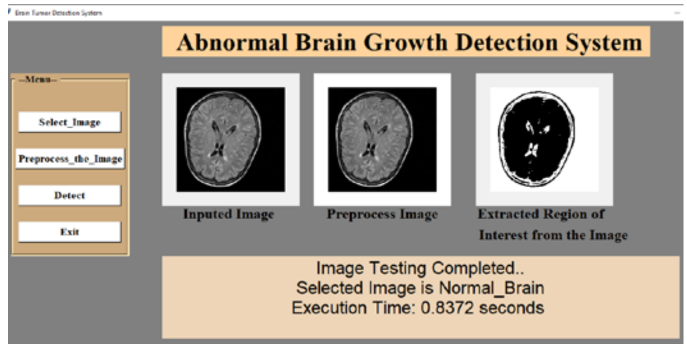

Figure 5. Classification of Abnormal Brain Growth as Normal

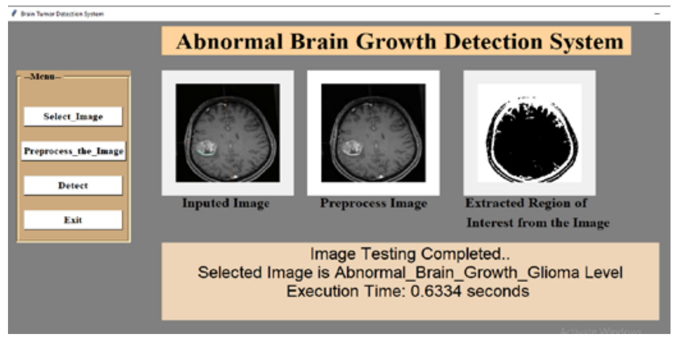

Figure 6. Classification of Abnormal Brain Growth as Glioma

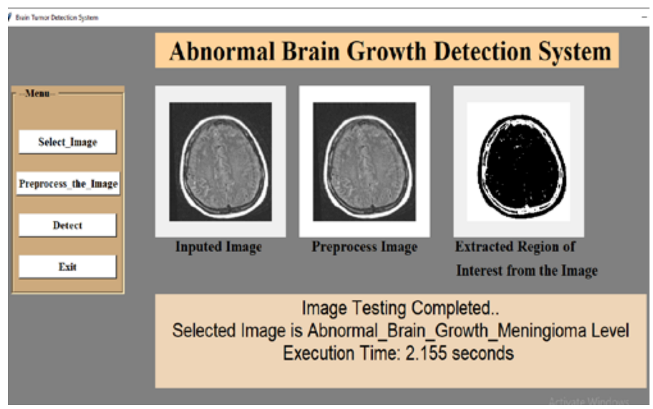

Figure 7. Classification of Abnormal Brain Growth as Meningioma

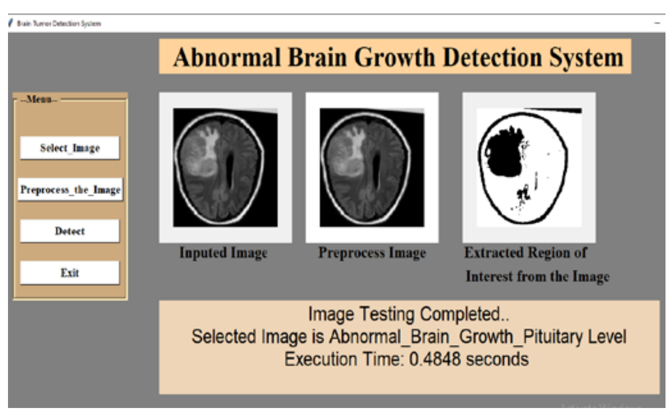

Figure 8. Classification of Abnormal Brain Growth as Pituitary

smooth spread within the central nervous system. Regrettably, the challenging nature of these abnormal brain growth lies in their aggressive behavior and tendency to disseminate quickly. Unfortunately, there is currently no known cure for high-grade gliomas. The aggressive nature of these abnormal brain growth makes them particularly difficult to treat comprehensively. Medical interventions for high-grade gliomas particularly focus on managing symptoms, slowing down the progression of the disease, and improving the individual's quality of life. This emphasizes the critical need for ongoing research and advancements in medical science to develop more effective treatments. Above five algorithms table describes that glioma abnormal brain growth frequently occurs at the time of calculating accuracy.[32]

In cases where meningioma displays signs of growth or activate symptoms, surgical interruption may be recommended by healthcare providers. The primary goal of surgery is the complete removal of the meningioma. Fortunately, meningiomas are generally classified as benign abnormal brain growth, meaning they are not cancerous, and in many cases, they are curable through surgical procedures. The surgical path aims to eliminate the abnormal brain growth, addressing both the symptoms and the potential for further growth. This form of intervention is considered effective and offers a positive prognosis for individuals diagnosed with meningiomas. It emphasizes the importance of timely medical attention and the potential for successful treatment when meningioma's exhibit signs of progression. Above five algorithms table describes that meningioma brain abnormal brain growth frequently occurs as much compared to glioma abnormal brain growth at the time of calculating accuracy.

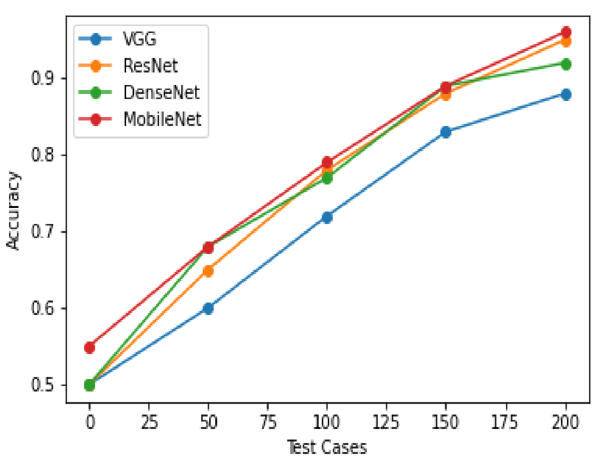

Figure 9. Graph of Test Cases versus Accuracy of each CNN Model

Identifying a pituitary abnormal brain growth at an early stage is important, as it offers the opportunity for successful treatment and control. Early detection significantly improves the chances of a cure or effective management. It's important to note that pituitary abnormal brain growth are generally considered curable, especially when diagnosed in their initial phases. Timely mediation enables healthcare professionals to implement appropriate treatment strategies, which may include surgical removal or other targeted therapies. The emphasis on early detection underscores the positive outcomes and the potential for a favourable prognosis in addressing pituitary abnormal brain growth. These highlight the importance of regular medical check-ups and prompt medical attention when symptoms arise, contributing to the overall effectiveness of managing and treating pituitary abnormal brain growth. Above five algorithms describes that pituitary abnormal brain growth frequently occurs as much compared to glioma abnormal brain growth and meningioma abnormal brain growth at the time of calculating accuracy.

Various CNN classification models, including VGG, ResNet, DenseNet and MobileNet, are employed for abnormal brain growth detection. The models are trained using 80% of the dataset, and the remaining 20% is reserved for testing. The classification results from each model are combined through ensemble techniques, and the final decision is based on majority voting. This approach incorporates multiple accuracy measures to enhance the overall precision in identifying abnormal brain growth.

$$\text{Accuracy} = \frac{\textit{Total number of Test Cases}}{\textit{Number of Correct Test Cases}} \times 100$$

Table 3. Accuracy of Classification Models Trained

Classification Algorithms	Accuracy
VGG(Visual Geometry Group)	0.880000
ResNet(Residual Neural Network)	0.910000
DenseNet(Densely Connected Convolutional Network)	0.900000
MobileNet(Mobile and Embedded Vision Application)	0.920000

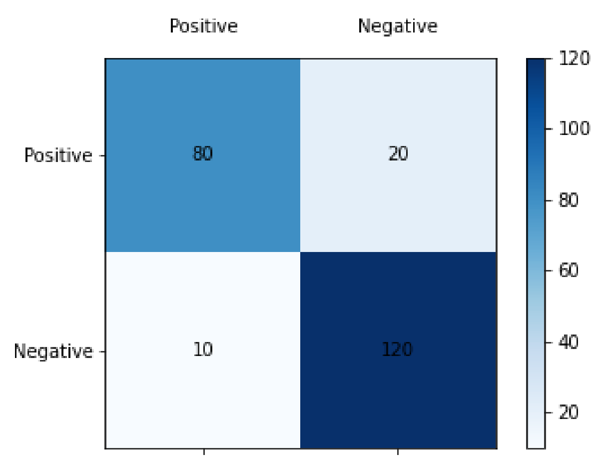

Figure 10. Confusion Matrix

Specifically, the Convolutional Neural Network (CNN) demonstrated notable success in accurately identifying abnormal brain growth. This robust performance establishes CNN as a highly suitable algorithm for this critical task. The substantial dataset size and the resulting high accuracy lend credibility to the reliability of CNN in practical applications, emphasizing its potential as a valuable tool in the field of medical image analysis. In research, the abnormal brain growth detection using four distinct algorithms: Visual Geometry Group (VGG), Residual Neural Network

(ResNet), Densely Connected Convolutional Network (DenseNet) and Mobile and embedded vision application (MobileNet).

CONCLUSION

The developed MRI abnormal brain growth detection system proves to be highly valuable for pathologists in effortlessly identifying and categorizing the presence of abnormal brain growth without the need for manual intervention. The system employs an ensemble approach, utilizing multiple instances of the VGG, ResNet, DenseNet and MobileNet model with varied initializations. This ensemble strategy enhances accuracy by reducing over fitting and promoting robustness against noise and outliers in the training data. By combining predictions from diverse models, the system demonstrates improved performance compared to a single model, ultimately increasing the precision of MRI abnormal brain growth detection. The success of this ensemble approach highlights its effectiveness in providing reliable and accurate results for the crucial task of abnormal brain growth detection in MRI scans. To further enhance the system, future considerations could involve expanding the dataset and incorporating both intensity-based and texture-based features.

CONFLICT OF INTEREST STATEMENT

The authors declare that none of them has any conflict of interest.

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