MINOR PROJECT

REPORT

on

Enhanced Brain Tumor Detection Using a Lightweight CNN Model

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ABSTRACT

This study presents a lightweight Convolutional Neural Network(CNN) model, designed to detect and classify brain tumors using MRI images. The model uses a dataset from Kaggle, comprising 7023 images in total, labelled into four classes: glioma, meningioma, pituitary and non-tumor. We preprocessed the data using techniques such as image resizing, normalization, grayscale conversion, and data augmentation to increase the size of our dataset, and make the model robust. The CNN architecture comprises 16 layers that includes - convolutional, max pooling, dropout, flatten, and dense layers. For model training, we used an adam optimization function which gave 98.20% accuracy on the test dataset. Evaluation metrics - precision, recall and F1-score validates the performance of our model, with precision scoring 98.24%, recall 98.18% and F1-score 98.18%. We further present a comprehensive analysis of the model's training and validation process through epochs vs loss and accuracy plots, confusion matrix and histogram of training and validation accuracy. The model we propose promises good results, and showcases itself as an effective tool for brain tumor detection and classification.

Keywords: MRI Images, Image Processing Techniques, CNN Technique

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1 Preface

The medical specializations of oncology and neurology encounter substantial challenges in the identification and treatment of brain tumors. The ongoing advancements in medical technology have resulted in a growing emphasis on the use of innovative and fresh techniques to enhance the precision and efficacy of tumor diagnosis. The purpose of this research is to develop a reliable automated model that can detect brain malignancies by examining the field of medical imaging, with a particular emphasis on magnetic resonance imaging (MRI) images. We are endeavoring to expand the current endeavors to improve the diagnostic capabilities of neuroimaging by integrating cutting-edge image processing techniques with machine learning algorithms. [1].

2 Background

2.1 Brain Tumors and Imaging Modalities

Brain tumors, a broad category of neoplasms, may be caused by a diverse array of cells in the central nervous system. Treatment planning and prediction are significantly dependent on their identification and characterization.

2.2 Need to Shift Towards Automated Tools

Traditionally, the identification of brain tumors has been heavily reliant on the manual evaluation of MRI images by medical specialists, who possess a wealth of experience and knowledge. Although effective, this approach is subjective, susceptible to human error, and occupies a significant amount of time, which may result in misdiagnoses and delays in the commencement of treatment.

Therefore, in recent years, the conventional approach has shifted in favor of the use of automated techniques to aid radiologists in the evaluation of medical images. These technologies integrate advancements in artificial intelligence, machine learning, and image processing to identify microscopic anomalies that may indicate the presence of malignancies. By extracting quantitative characteristics and patterns from MRI data, these algorithms have the potential to decrease interpretation time, enhance diagnostic accuracy, and promote early intervention.

2.3 Methods in Automated Brain Tumor Detection

A variety of methodologies have been investigated, including fundamental image processing methods such as feature extraction and picture segmentation. These methods attempt to extract valuable information from MRI images, including tumor shape, texture, and intensity patterns, and then apply this information to distinguish between areas that contain tumors and those that do not.

2.4 Types of Brain Tumor

- **Glioblastoma multiforme (GBM):** This aggressive glioma type is associated with a poor prognosis and is difficult to treat effectively. It is prone to rapid development and dissemination as a 4th-grade astrocytoma.

- **Meningioma:** These tumors are benign and typically slow-growing, originating from the meninges. Nevertheless, it is essential to conduct an early diagnosis to monitor progress and take appropriate action to prevent issues.

- **Pituitary adenoma:** This type of tumor develops in the pituitary organ. Hormone synthesis and regulation are impaired by this tumor. Therefore, the early detection of pituitary adenomas enables the prompt treatment of hormonal abnormalities.

- **Acoustic neuroma (Vestibular Schwannoma):** These tumors are produced in the vestibular nerve, which is essential for hearing. This tumor is also frequently benign; however, the early identification of acoustic neuromas is crucial for the preservation of hearing function and the prevention of adverse effects, such as facial paralysis or weakness, which are associated with tumor progression.

3 Introduction

A brain tumor is characterized by the abnormal proliferation of cells or their mass growth in or around the brain. The brain's health and functioning are influenced by the size and location of the tumor, which can be either benign (non-cancerous) or malignant (cancerous)[2] As a result of these factors, even benign tumors can cause discomfort if they expand and exert pressure on the surrounding nerves, blood vessels, and tissues. Brain tumors are diagnosed in approximately 40,000 to 50,000 individuals annually, which accounts for 20% of the juvenile population.[3]

The early detection of brain lesions is beneficial in the extension of human life. It enables medical professionals to offer effective treatment options and initiate treatment at a stage where the tumor is curable.[4]The versatility and potential of this approach are demonstrated by the focus on Glioma, Meningioma, and Pituitary among the over 150 different types of brain tumors.[5][6] Each tumor type necessitates a unique treatment strategy, and the best possible treatment can be determined by the doctors if they can accurately identify the exact type, location, and extent of the tumor. To address this challenge, a CNN architecture that is both accurate and lightweight has been developed.

Although traditional methods are already in place, the question of why there is a need for AI/ML techniques arises. The existing methods are valuable, but they lack speed and accuracy. AI models can analyze a vast amount of image datasets and provide more accurate results more quickly, reducing the likelihood of misdiagnosis.[7] This is due to the availability of highly efficient computational systems. (ML) Machine learning and (DL) deep learning have gained increasing popularity in the past few years). For sectors such as electronics, economics, and biomedicine, ML algorithms are a revolutionary technology.[8] The researchers have capitalized on the strengths of ML, making the most significant contributions to medical applications. The image analysis process is expedited by ML algorithms, which enables the quicker identification and categorization of the tumor. The integration of ML with biomedical research has demonstrated a significant improvement in healthcare as the world continues to witness the evolution of ML techniques.[9] These models can significantly enhance the differentiation between various types of tumors in a shorter amount of time, in contrast to the time-consuming traditional methods. In addition, the traditional methods may result in errors in diagnosis and treatment, as the interpretation of MRI scans may be subjective and may vary among clinicians.

3.1 Project Phases

The undertaking has been divided into three primary phases:

1. **Phase I:** Implemented numerous pre-processing techniques on a dataset consisting of 253 photographs. Developed a Convolutional Neural Network (CNN) model that was fed with the preprocessed images from each of the approaches and the results were compared.

2. **Phase II:**A state-of-the-art model is constructed with a focus on reducing the number of parameters to less than 1 million and increasing the accuracy to over 95%. The dataset that was employed in this phase comprises 7023 photographs.

3. **Phase III:** The final stage involves the development of a user-friendly online application that provides the user with information regarding brain tumors, their treatment, and symptoms. The user is also able to input the MRI to predict the presence of a brain tumor.

4 Literature Survey

In 2023, Sarajit Das conducted research that employed Transfer Learning in conjunction with a Convolutional Neural Network. This study utilized MRI images from Kaggle (Masoud Nick-parvar), (A. Hamada), which comprised 7023 segments and were classified into four categories: pituitary, glioma, meningioma, and no tumor. The total dataset was divided into the training, validation, and testing sets, which accounted for 90%, 5%, and 5% of the dataset, respectively. Several top layers were frozen in this research, and subsequently, additional layers were injected to achieve an accuracy of 99.61%. The EfficientNet framework was employed in this study.[7]

N. conducted a research in 2023. To classify preprocessed MRI brain tumor images, Remzan implemented a Convolutional Neural Network (CNN). MRI scans from a dataset provided by Masoud Nickparvar, consisting of 7019 images divided into four groups: 1620 glioma images, 1644 meningioma images, 1756 pituitary images, and 1999 normal images. It implemented three convolutional layers, each of which was succeeded by a dropout layer and maxpooling. There are 1.5 million parameters utilized in this CNN technique. The model achieves an accuracy of 95.65%[10]

In 2023, Beyza Nur TU¨ ZU¨ N concluded a project that involved the development of a Convolutional Neural Network (CNN) for the classification of brain tumors. The network was trained on MRI scans obtained from Kaggle (Masoud Nick-parvar). The dataset consisted of 7022 images, with 78% and 22% of them being divided into training and testing. It utilizes four convolutional layers, followed by a maxpooling layer, a dropout layer, a flatten layer, and, finally, a fully connected layer. This used four alternative models: GoogleNet, which has 22 layers, MobileNetV2, which has 3.4 million parameters and 53 levels, InceptionV3, which has 23.8 million parameters and 48 layers, and EfficientNet b0, which has 5.3 million parameters and 237 layers.. The EfficientNet b0 model was trained on 100 epochs, resulting in the highest possible result values of 99.54

In 2024, Gu¨ler conducted a study that utilized a dataset sourced from the Brain Tumor MRI dataset on Kaggle. This dataset comprises 7022 brain MRI images that are categorized into four categories: gliomas (1321 images), malignant tumors (1339 images), pituitary tumors (1456), and normal tissues (1595 images). The dataset was employed to classify brain tumors. 60% of the dataset was designated as a training set, while 40% was designated as a testing set. It utilized DenseNet and SqueezeNet, as well as VGG and ResNet designs with 41 and 152 layers, respectively. DenseNet achieved the highest accuracy of 85% when combined with an SVM classification method among these four architectures that utilized machine learning techniques.[11]

A study conducted by Syed Ahmmed in 2023 used deep learning frameworks for the classification of brain tumors using MRI images. The research worked on two architectures: ResNet 50 and Inception V3. It used 2 distinct datasets. The first dataset consisted of 3459 MRI scans containing 4 classes(glioma, meningioma, non-tumor, and pituitary) and the second dataset consisted of 3000 images with 2 classes (tumor present and tumor absent). ResNet 50 and Inception V3 are the 2 models used. An accuracy of 97.68% for the multi-class dataset and accuracy rate of 99.84% was achieved for the binary dataset.[12]

In 2021, Agus Eko Minarno conducted research that proposed a Convolutional Neural Network (CNN) approach to the classification of brain cancers, which included glioma, meningioma, pituitary tumors, and no malignancies. The dataset employed in this study consisted of 3,264 MRI scans, which included 926 images of glioma, 937 images of meningioma, 901 images of the pituitary, and 500 images of non-tumor images. The CNN design consisted of five conv2D layers, each followed by a dropout layer and maxpooling. Following this, the first dense layer with a relu activation function and the second dense layer with a softmax activation function were implemented. A dropout layer was inserted between these dense layers. The highest accuracy was achieved at 96% in this study, which tested three model scenarios with a variety of parameters.[[4]

Brain malignancies were identified in MRI scans by Soheila Saeedi in a 2023 study that employed machine learning techniques. The dataset employed in this investigation consisted of 3264 T1-weighted images. The contrast-enhanced MRI images consist of 926 glioma images, 937 meningioma images, 901 pituitary images, and 500 non-tumorous brain images. A 2D CNN model with 243,924 parameters and 28 layers is employed in this investigation. Convolutional auto-encoder neural networks are an additional model that is implemented. The 2D CNN has an accuracy rate of 93.44%.[13]

Research done by P Gokila Brindha in 2021 addresses the problem of distinguishing between tumor and non tumor brain MRI image. The dataset consists of 2065 images labelled as “Yes” and “No” in JPG format. This dataset is used in ANN architecture with a total of 7 layers and in CNN se-sequential model with 6 layers. This study explores the use of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) models. These models aim to aid radiologists in making fast decisions. The accuracy achieved in ANN is 80.77% and CNN is 89% respectively, surpassing many existing methods and demonstrating its efficacy in brain tumor classification[14]

Therefore, we can infer that the accuracy of the aforementioned articles ranges from 85% to 99.84%, and the model’s complexity increases significantly, reaching up to 23.8 million parameters. Our research demonstrates a promising accuracy of 98.09% with a model that contains parameters below 1 million, thereby minimizing the need for computational resources, in light of all of these findings and conclusions.

5 Objective

The primary objective of this project is to provide a comprehensive examination of the pre-processing methods utilized for MRI images and the development of a Convolutional Neural Network (CNN) model that is designed to facilitate the early diagnosis of brain tumors in patients. This study evaluates and analyzes the impact of a variety of preprocessing methods on the quality and precision of magnetic resonance imaging (MRI) images.

Additionally, this investigation concentrates on the development of a Convolutional Neural Network (CNN) model that is both lightweight and exhibits promising accuracy. The goal is to develop a model that can identify brain malignancies at the forefront of the field while utilizing the fewest computing resources possible.

Ultimately, a user-friendly and straightforward interface is developed, enabling users to submit an image of an MRI scan of the brain. Our system analyzes the scan and provides a precise result after it is submitted. This suggests that consumers can immediately determine whether they have a brain tumor by submitting their MRI image.

6 Dataset

6.1 JPG Datset - 1:

The dataset is composed of a diverse collection of medical images in JPG format (Joint Photographic Group). There are a total of 253 images in the dataset, which is further classified as ”no” (absence of brain tumor) and ”yes” (presence of brain tumor).[14]

6.2 DICOM Dataset:

The DCM format, a widely used standard in the healthcare industry, is used to save medical images in the DICOM (Digital Imaging and Communications in Medicine) picture library. Metadata, including patient information, acquisition parameters, and picture orientation, is included in each file in addition to the pixel data.

6.3 JPG Datset - 2:

The dataset is composed of a diverse collection of medical images in JPG format (Joint Photographic Group). The dataset is further classified into four categories: ”glioma,” ”meningioma,” ”notumor,” and ”pituitary.” In total, there are 7023 images

Table 1: DCM File Information

Attribute	**Value**
Manufacturer	
Institution Name	
Referring Physician Name	
Patient Name	
Patient ID	002_s_0296
Patient Birth Date	Not Available
Patient Sex	M
Patient Weight	75
Body Part Examined	BRAIN
MR Acquisition Type	2D
Imaging Frequency	127.77876
Slice Thickness	3.313
Repetition Time	3000

7 Design

7.1 Phase - I

- For this investigation, we collected two distinct categories of labeled datasets in jpg and dcm formats. ”YES” and ”NO” are the two classes in the JPG file.[14]
- In order to preprocess the images, procedures such as image scaling, normalization, thresholding, interpolation, sharpening, and denoising are employed. This process enables the precise identification of tumors and enhances the lucidity of the images
- Enhancement techniques are employed to high- light minute features in the image that may suggest the presence of a tumor. The techniques in question are adaptive histogram equalization, histogram equalization, and contrast elon-gation.
- Finally, we employed the preprocessed MRI data to train the CNN model, which enabled us to ascertain whether the patient had a brain malignancy.

The following areas are evaluated in this investigation in order to achieve this:

1. **Image Preprocessing:** To achieve a more accurate interpretation, the MRI images undergo a series of preprocessing phases. This procedure involves the following steps: normalization to ensure that pixel intensity values

remain consistent, resizing of images for standardization, thresholding to segment regions of interest, interpolation to align spatial dimensions, sharpening techniques to enhance edges, and denoising to reduce image noise.

2. **Image Enhancement:** In addition to preprocessing, image enhancement methods are implemented to enhance the diagnostic value and visual lucidity of MRI images. This method was further improved by Histogram Adaptive Equalization and Adaptive Equalization, which responded to local picture properties, resulting in a more effective enhancement.[15]

3. **Feature Extraction:**The MRI images are analyzed to extract significant characteristics that suggest the presence of a brain tumor after undergoing preprocessing and enhancement. The objective of feature extraction methods is to recognize distinctive patterns and properties within the visuals, including intensity, texture, and form. These methods are essential for the identification and classification of tumors.[15]

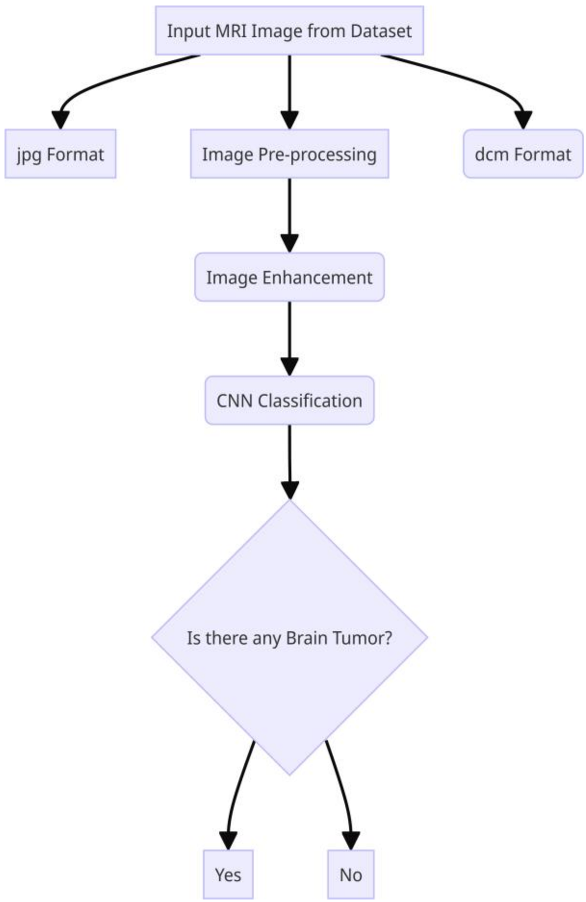


Figure 1: Flow Chart

7.2 Phase - II

- For this project, we implemented the *jpg* format, which consists of four classes: ’glioma’,’meningioma’, ’non-tumor’, and ’pituitary’.

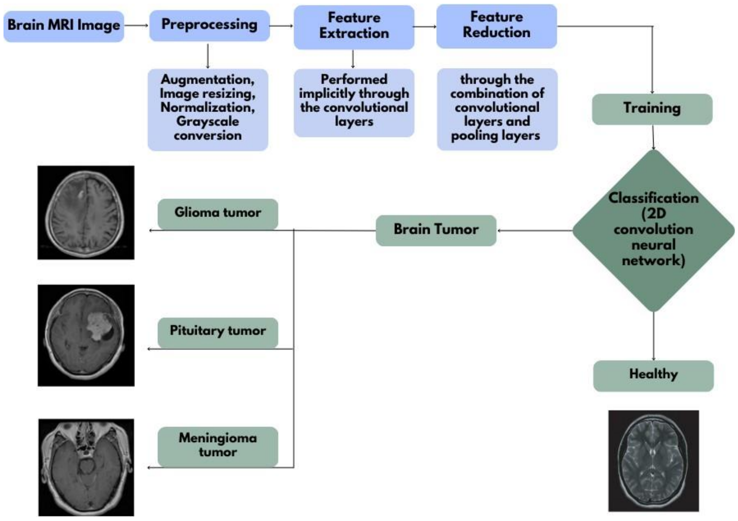


Figure 2: Flow Chart

- Image scaling, normalization, and thresholding are implemented to enhance the lucidity of the images and facilitate precise tumor identification.[10]

The following areas are evaluated in this investigation in order to achieve this:

1. **Image Preprocessing:** In order to improve the quality of the images and achieve a more accurate interpretation, the MRI images undergo a series of preprocessing phases. These processes include normalization to maintain the consistency of pixel intensity values, re-sizing of images to ensure uniformity in the dataset, and grayscaling the dataset to restrict the number of channels to one.

2. **Feature Extraction:** The MRI images are analyzed to extract significant characteristics that suggest the presence of a brain tumor after undergone preprocessing and enhancement. The objective of feature extraction methods is to identify distinctive patterns and qualities in the images, including intensity, texture, and form. These methods are essential for the identification and classification of malignancies.

7.3 Phase III

The project is also dedicated to the development of a user-friendly platform to ensure that all individuals have access to the research results and valuable tools, in addition to the study on brain tumor detection and the increasing importance of digital technologies in healthcare. The web application (web app) functions as a centralized repository for technologies, resources, and information related to the identification of brain tumors. The following sections are included:

1. Home
2. Treatment
3. Work
4. Contact

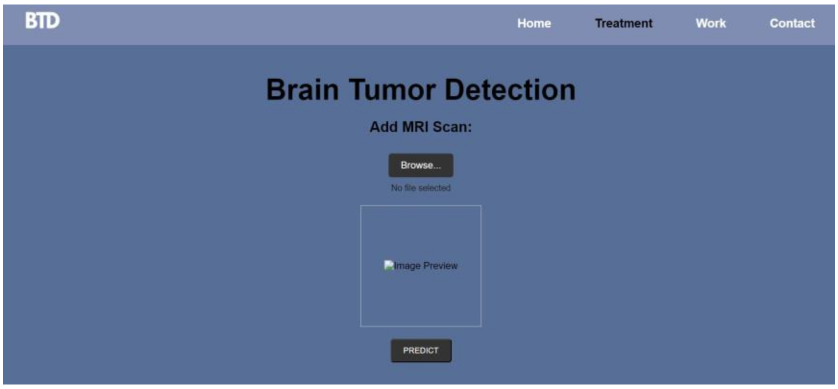


Figure 3: Web Application

7.3.1 Home

This section offers a comprehensive comprehension of brain tumors. The online application provides users with exhaustive information regarding brain tumors, such as their causes, types, symptoms, and associated risks.

7.3.2 Treatment

The primary objective of the information presented in this section is to assist in the selection of brain tumor treatment options. Users are capable of acquiring information regarding the necessary procedures and treatments. Furthermore, this section contains a Detect function that is connected to the backend. CNN will analyze an MRI scan image to ascertain whether or not the patient has a malignancy. Users just need to submit the image.

7.3.3 Work

All research related to the initiative is displayed in the Work section. Users have access to the team's research papers, publications, and ongoing initiatives.

7.3.4 Contact

Finally, we provide users with all the details they might need to contact the teams, such as Contact numbers and Email addresses. Users can also send their related queries and feedback through the contact form provided in this section

8 Implementation

8.1 Preprocessing

Preprocessing is the initial stage of digital image processing that enhances their quality. When the resolution of the MRI image is subpar and it is challenging to determine the regions of the brain where the tumor is situated. Preprocessing improves the quality of photographs, which simplifies the process of interpreting them. The purpose of each preprocessing phase that was implemented is detailed in Table II. [1]

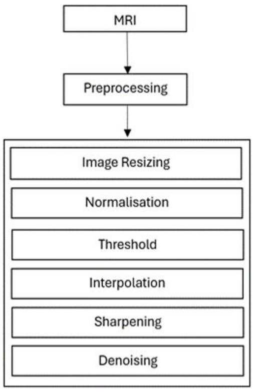


Figure 4: Preprocessing Steps

Table 2: Preprocessing Step

Preprocessing Step	Aim
Image Resizing	Recent research has focused on content-aware resizing methods, aiming to adapt image dimensions while protecting essential content.
Normalization	Normalization is crucial for making sure pixel values are consistent and easy to analyze, especially in the context of MRI brain tumor images.
Threshold	Image thresholding plays a vital role in improving the interpretability of MRI images, providing a foundation for subsequent image processing tasks such as edge detection and pattern recognition.
Interpolation	Image interpolation facilitates the seamless adjustment of MRI images, ensuring that the transformations are accurately represented.
Sharpening	Image sharpening ensures that the edges become more pronounced and easily distinguishable, thereby providing a sharper appearance to the MRI images.
Denoising	Effective denoising is crucial for enhancing the clarity of MRI images which enables accurate identification of abnormalities in the brain.

8.1.1 Image Resizing

Image resizing is the process of modifying the dimensions or proportions of an image. It involves modifying the image's dimensions by manipulating the number of pixels used to represent it. Photos of varying sizes are included in our collection. The computer is able to process items more efficiently when they are resized to a standard dimension, which maintains uniformity. The preparation and analysis activities can be expedited by reducing the size of large photos. Additionally, it facilitates the process of narrowing in on photographs.

8.1.2 Normalization

A critical stage in the enhancement of MRI brain tumor images is normalization. Normalization is essential in the field of medical imaging, particularly with MRI scans, to guarantee that pixel values are consistent and easy to assess. It is essential to adjust the pixel intensities to a specific range when conducting a search for brain lesions. This facilitates our comprehension of the visual attributes. The standard formula for normalization converts the original pixel values (r) to normalized values (s) by employing the following:

$$s = \frac{r - MinPixelV\ alue}{MaxPixelV\ alue - MinPixelV\ alue}$$

In this section, we determine the minimum and maximum pixel values from the entire collection of photographs. Normalization not only addresses variations in image intensity but also establishes a consistent scale. This scale provides a robust foundation for future image processing operations, such as feature extraction and segmentation. The application of normalization to MRI brain tumor images significantly improves the quality of the images and guarantees the reliability of the findings in the field of medical image processing.

8.1.3 Threshold

As a fundamental and dependable preprocessing instrument, thresholding is evident. Serving as an image segmentation technique, it simplifies the intricate grayscale information by converting the MRI image to a binary representation, enabling the separation of foreground (objects) and background.

of relevance, such as malignancies) and heritage. The method involves the categorization of each pixel according to its intensity in relation to a predetermined threshold value, thereby converting the image to binary black-and-white. The identification and isolation of essential characteristics within the brain scan are enhanced by this binary conversion, which promotes simplified analysis. Image thresholding is essential for the enhancement of the interpretability of MRI images, as it serves as a foundation for additional image processing tasks, including pattern recognition and edge identification. This technique not only enhances the efficacy of computer vision but also simplifies the visual representation of the MRI scan [16]

8.1.4 Interpolation

Image interpolation is a fundamental preparatory technique that enables the scaling, translation, and orientation of images to facilitate more comprehensive analysis. This method is particularly important in applications such as medical imaging, which requires precise alignment with anatomical references, and remote sensing, which requires cartographic referencing. The grid points are misaligned as a result of the geometric adjustments made to the images, necessitating the use of interpolation procedures. There are two categories of interpolation techniques: adaptive and non-adaptive. Adaptive algorithms dynamically adjust to the material being interpolated and distinguish between delicate textures and pointed outlines in the brain scan. In contrast, non-adaptive methods provide a standardized approach by consistently managing all pixel values. The seamless correction of MRI images is facilitated by image interpolation, which guarantees that the transformations are accurately represented. This subtle adjustment enhances the interpretability of brain imaging, thereby assisting medical professionals in the precise identification of potential anomalies.

8.1.5 Sharpening

Image sharpening is a substantial preprocessing technique that is designed to enhance the visual lucidity of critical components. It is distinguished from a cosmetic touch-up in that it emphasizes the enhancement of edge definition, which is particularly important in situations where the background and margins of drab photographs lack a clear contrast. Sharpening guarantees that the margins are more prominent and easily identifiable, thereby providing the MRI images with a more defined appearance. This enhancement is essential for the purpose of enhancing the interpretability of the images and enabling medical professionals to more accurately identify and assess potential abnormalities, such as brain tumors. Image refinement functions as a corrective lens, enhancing the focus of MRI images and enabling a more precise assessment of critical features in brain imaging.

8.1.6 Denoising

Image denoising is a critical preparatory procedure. The quality of MRI images is significantly improved by effective denoising, which enables the accurate diagnosis of brain disorders. This method is comparable to meticulously removing extraneous markings from a drawing while preserving essential elements, thereby eradicating undesired anomalies or ”noise” from the photographs. Noise is the term used to describe the interruptions that occur when electronic data is transmitted through cables, satellites, or wireless connections due to signal disturbances.

8.2 Image Enhancement Techniques

Table 3: Image Enhancement Techniques

Image Enhancement Techniques	Explanation
Contrast Stretching	Contrast stretching acts as a metaphorical spotlight that intensifies the visibility of potential abnormalities in MRI images.
Histogram Equalization	Histogram Equalization enhances global contrast, suitable for improving the visibility of details in various intensity levels
Histogram Matching	Histogram equalization enhances the differentiation between healthy tissue and tumors, providing a clearer and more detailed representation of MRI scans by redistributing pixel intensities.
Adaptive Histogram Equalization	AHE adjusts the intensity distribution in a spatially adaptive manner, addressing variations in brightness and contrast across different regions of the MRI scans.

8.2.1 Contrast Stretching

It is akin to adjusting the exposure on a photograph; its objective is to reveal concealed elements. This method dynamically extends the intensity lev- els of the image to encompass the desired spectrum. This modification assigns a distinct digital number to each pixel, primarily to emphasize minute details that may be challenging for humans to discern. Contrast stretching functions as a metaphorical floodlight that enhances the visibil- ity of potential anomalies in MRI images. It functions in a manner comparable to adjusting the parameters of a camera to ensure that critical information is not overlooked. This enhance- ment facilitates the interpretation of brain imaging by medical professionals and enhances theirprecision.

8.2.2 Histogram

A histogram is a graphic representation that illustrates the distribution of luminance levels in a digital image. The histogram for a grayscale image with values ranging from 0 to $L-1$, is represented by a discrete function denoted by $h(r_k) = n_k$.
In this instance, the grayscale level is represented by r_k and the number of pixels in an image that have a specific grayscale level is represented by n_k The histogram is a critical element in a variety of spatial image processing techniques. Modifying the histogram can significantly enhance the quality of the image.[17] [18]

8.2.3 Histogram Equalization

Histogram Equalization (HE) is a widely used technique for improving visual contrast. It endeavors to achieve a more equitable distribution by redistributing the grayscale values in a photograph. The objective is to generate a symmetrical histogram that corresponds to each grayscale value with an equal number of pixels. To accomplish this, the procedure implements a transformation function, as illustrated in the following:

The mathematical expression for this transformation is given by the equation: $s = T(r)$. The inverse transformation can be employed to retrieve r from s.[17]

$$r = T^{-1}(s), \textit{ where } 0 < s < 1$$

8.2.4 Adaptive Histogram Equalization

Adaptive Histogram Equalization (AHE) is comparable to Histogram Equalization. It concentrates on minute regions to modify the luminance of the image. This is a computer image processing technique that involves the adjustment of the luminance values of the image. It consists of numerous histograms, each of which represents a distinct area of the image. Consequently, it is distinct from histogram equalization and can be employed to enhance the borders in each zone and increase contrast. The pixels in the image will be customized in accordance with the pixels in the surrounding area. A contextual region is an example of such an area. AHE has the capacity to exacerbate noise in homogeneous regions of a picture.[17]

8.3 Model - I

The dataset has been partitioned into three sections in.jpg format:

1. Train
2. Validate
3. Test

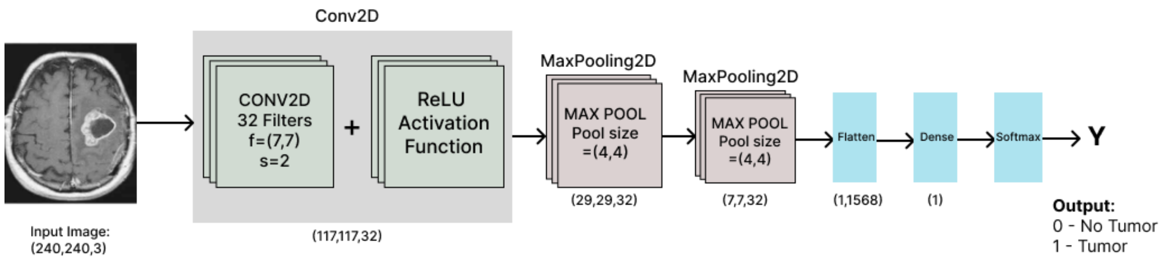


Figure 5: Model - I Architecture

The *.jpg*dataset contains 253 photographs, which are categorized as 177 (Training dataset), 38 (Validate Dataset), and 38 (Test Dataset). The dataset is input into the model using the architecture depicted in Figure (3) after preprocessing and picture enhancement are completed. We employed a fundamental CNN model for the model, as our dataset consisted of only 253 photographs. The activation function is ReLU, and each input image is inserted into a neural network with a single convolutional layer. The images are in the format of (240, 240, 3). Convolutional layers generate an image of the form (117,117,32), which is subsequently reduced to (7,7,32) by two Max Pooling layers. Additionally, we implemented a Softmax activation function, a Flatten layer, and a Dense layer to achieve classification. Each stratum is described in detail below:[2]

- A convolutional layer consisting of 32 filters, each of which has a dimension of (7, 7) and a striding of 2.
- A layer of activation for ReLU.
- A layer of maximum pooling with s=4 and f=4.
- An additional layer of Max Pooling with f=4 and s=4. flattening layer that reduces the 3D matrix to a 1D vector.
- A dense layer that is completely linked and contains a single neuron, as well as sigmoid activity

8.4 Model - II

The dataset employed in this investigation consisted of MRI images of varying diameters. In order to enhance the processing time and ensure uniformity within the dataset, each image was reduced to 120 by 120 pixels. Subsequently, each image was converted to grayscale and normalized simultaneously [19].

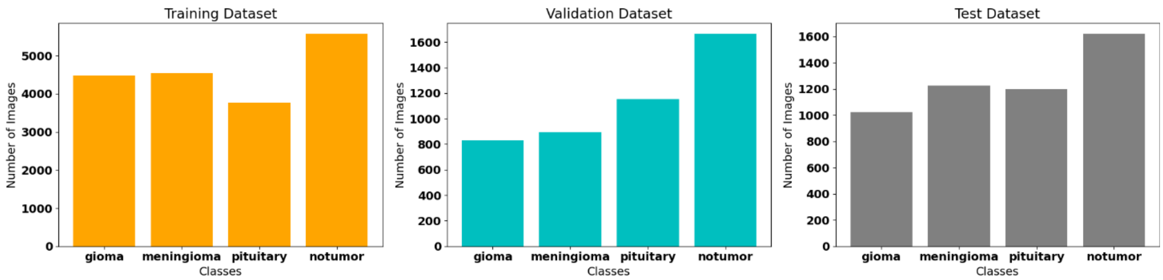


Figure 6: Split of the dataset into training, validation, and testing

The proposed model is composed of several layers, including convolutional, max-pooling, dropout, flatten, and dense layers. Figure 2 illustrates that this design employed a total of 16 layers, commencing with a convolutional layer that contained 16 filters, each of which measured 3 by 3. The padding and ReLU activation functions of this architecture were identical in each convolutional layer. The first layer was succeeded by a 2*2 max pooling layer, with a 2*2 interval between each max pooling layer. Rather than employing 16 filters, an additional convolutional layer was implemented, this time with 32 filters. It was supplanted by a batch normalization layer (0.5) and a 2*2 max pooling layer. The subsequent two levels were composed of 64-filter convolutional layers. These two layers were succeeded by an additional max pooling layer of size 2*2. Two additional convolutional layers with a filter size of 128 were implemented, followed by an additional max pooling layer. The dropout layer was implemented after each max pooling layer, except the second max pooling layer, to prevent overfitting.[5]

To guarantee that the model's learning capacity is balanced and that it can detect complex patterns without becoming overfit, a dense layer with 256 units was implemented. In the end, the four distinct classes in our dataset were represented

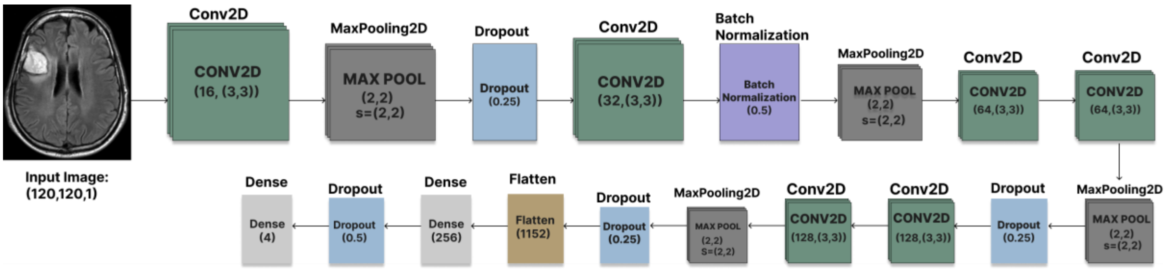


Figure 7: Model - II Architecture

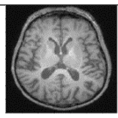
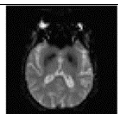
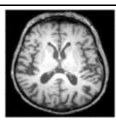
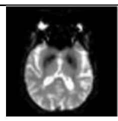
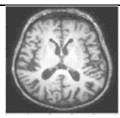
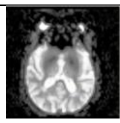
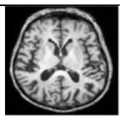
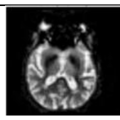
by an additional Dense layer with four units and a sigmoid activation function. [20] Adam was employed as an optimization function to enhance the model's efficacy.[20] The training was completed with a batch size of 64 and 100 epochs, except 0.0001, which had a decay rate of 0.77 per epoch. Various values were employed, including 0.1, 0.01, 0.001, 0.002, and 0.0001.[20] [21]

9 Experimental Results

9.1 Model - I

In the tables below, we have contrasted the results of four distinct preprocessing methods to ascertain which method achieves the highest level of accuracy. The most favorable outcomes are achieved by integrating Normalization, Adaptive Histogram Equalization, and Histogram Equalization.

Table 4: Experimental results of different image enhancement techniques

Image Enhancement Techniques	JPG Dataset	DICOM Dataset
Original Image		
Contrast Stretching		
Histogram Equalization		
Adaptive Histogram Equalization		

The impact of various image enhancement approaches is illustrated in Table 4, which compares the original picture from both datasets with the remedies that were applied to it. The results of the investigation are presented in Table 5.

Table 5: Model Accuracy and Loss

Parameters	Model-1(N)	Model-2(CS)	Model-3(HE)	Model-4(AE)
Test Loss	0.47	0.57	0.37	0.38
Test Accuracy	0.76	0.68	0.84	0.81
Validation F1 score	0.833	0.92	0.71	0.85
Test F1 score	0.836	0.73	0.874	0.84

The contrast stretching technique corrected the image's luminosity and enabled us to identify even the most minute details in the images. The histogram equalization method was employed to redistribute the grayscale value intensity of the image.

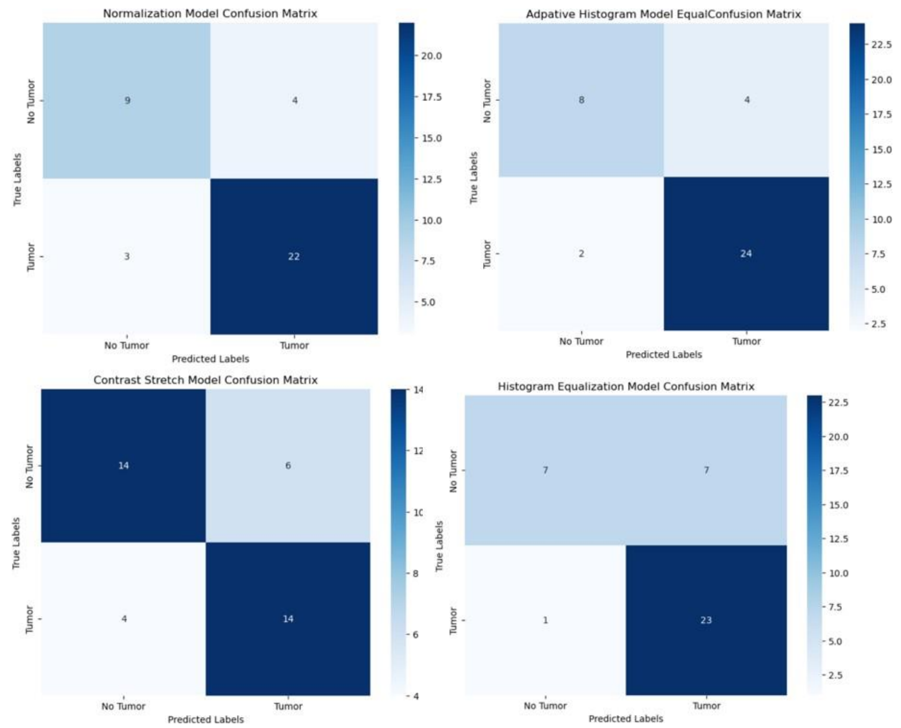


Figure 8: Confusion Matrix

Figure 8 illustrates the confusion matrix for each method. The Confusion Matrix of Histogram Equalization and Adaptive Histogram Equalization yields the most favorable outcome, as demonstrated.[22] Contrast Stretching, on the other hand, exhibits the lowest performance among all employed strategies.

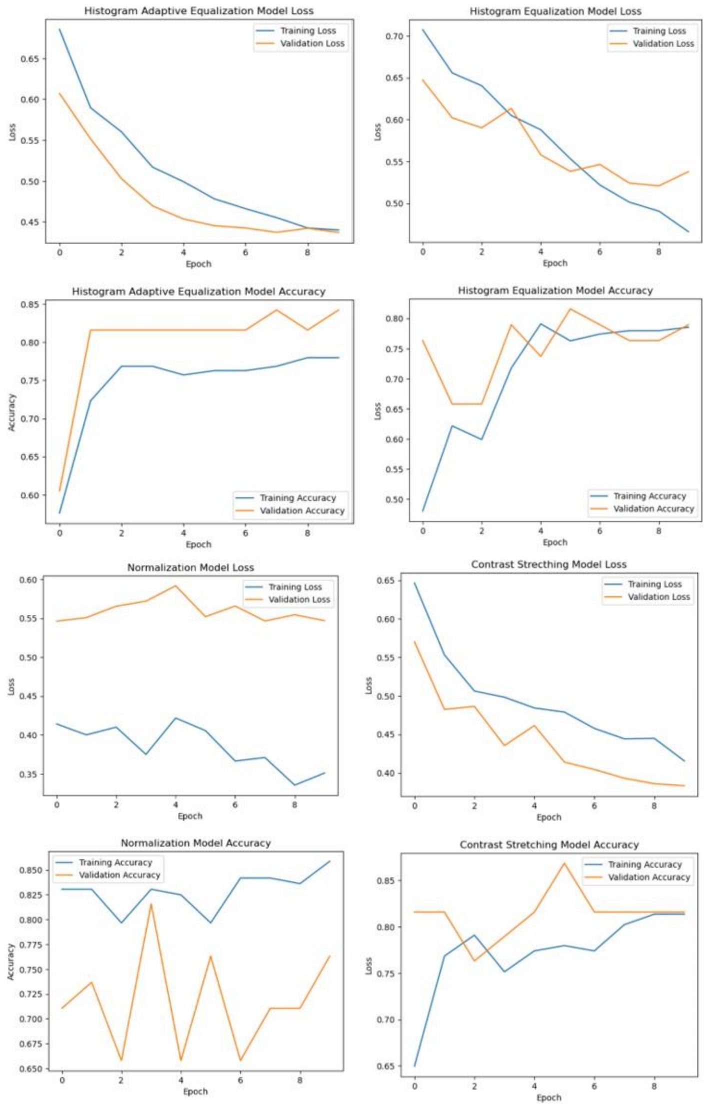


Figure 9: Accuracy and Loss Graph

The training accuracy, validation accuracy, training loss, and validation accuracy of each technique are illustrated in Figure 9.

9.2 Model - II

The model's performance on both the training and validation data is demonstrated by its training accuracy of 0.9967 and total training loss of 0.0096, which were achieved after 100 epochs of training, each of which took approximately 28 seconds to complete.[20] The validation accuracy and loss of 0.9947 and 0.0150, respectively, are indicative of the model's well-fitting to the training data.[10]

In conclusion, our test model produces favorable results on the test data, with an accuracy of 0.9820 and a loss of 0.0.906. Table 6 provides critical performance metrics for a classification model in three distinct datasets: training, validation, and testing.[11]

Table 6: Results obtained using the proposed CNN model

Parameters	Accuracy	Loss	Precision	Recall	F1-Score
Training Data	0.9967	0.0096	0.9968	0.9967	0.9965
Validation Data	0.9947	0.0150	0.9949	0.9945	0.9946
Testing Data	0.9820	0.0906	0.9824	0.9818	0.9818

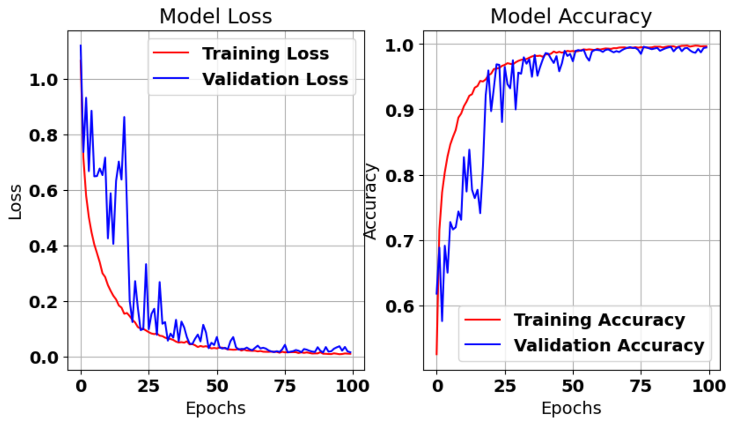


Figure 10: Accuracy and Loss Graph

The training accuracy, validation accuracy, training loss, and validation accuracy of each technique are illustrated in Figure 10.

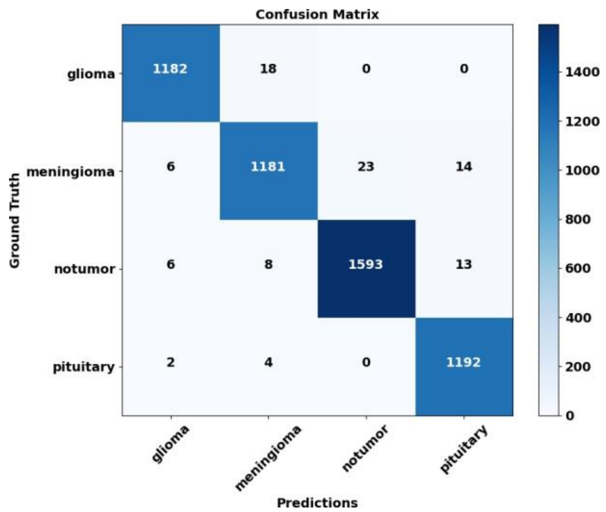


Figure 11: Accuracy and Loss Graph

Figure 11 illustrates the confusion matrix for each method. It is evident that our model is highly accurate, as evidenced by the low number of false positives and false negatives.

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