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on

Recognition of Medical Imaging Pattern Using Machine Learning and Deep Learning Techniques

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by

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ABBREVIATIONS

MRI - **M**agnetic **R**esonance **I**mage

SVM – **S**upport **V**ector **M**achine

ANN – **A**rtificial **N**eural **N**etwork

CNN – **C**onvolutional **N**eural **N**etwork

DWT – **D**iscrete **W**avelet **T**ransformation

PNN - **P**robabilistic **N**eural **N**etwork

KNN - **K**-**N**earest **N**eighbor

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ABSTRACT

The unprecedented improvements in computing capabilities and the introduction of advanced techniques for the analysis, interpretation, processing, and visualization of images have greatly diversified the domain of medical sciences and resulted in the field of medical imaging. The Magnetic Resonance Imaging (MRI), an advanced imaging technique, is capable of producing high quality images of the human body including the brain for diagnosis purposes. The Brain tumor is affecting many people worldwide. It is not only limited with the old age people but also detected in early age. Brain Tumor is the abnormal growth of cell inside the brain cranium which limits the functioning of the brain. Early detection of the brain tumor is possible with the advancement of machine learning (ML) and image processing. Medical image processing is the most challenging and emerging field today. Many scientists and researchers are working to develop and add more features to this tool. MRI Imaging plays an important role in brain tumor for analysis, diagnosis and treatment planning. It's helpful to doctor for determine the previous steps of brain tumor. Brain tumor detection using MRI images is a challenging task, because of the complex structure of the brain. This work is about detecting Brain tumors from MRI images using an ML model which is programmed in python using jupyter notebook. MRI image can be processed and the brain tumor can be segmented using various image segmentation techniques. The process of identifying brain tumors through MRI images can be categorized into four sections of image processing: pre-processing, image segmentation, feature extraction and image classification. In this proposed work we have developed a model for the partial fulfillment of the requirements to arrive at the best results that can help us to detect brain tumors in early stage.

Keywords: MRI, Image Processing, Python, Jupyter notebook.

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CHAPTER 1

INTRODUCTION

1. 1 Introduction

Since brain tumors are the most common tumors in humans, research on brain tumors is very important. It is the leading cause of death in children and adults. A tumor is defined as an abnormal growth of tissue. Brain tumors are generally divided into two groups: benign tumors and malignant tumors. MR imaging plays an important role in the analysis, diagnosis and treatment planning of brain tumors. Help doctors identify rapid growth of brain tumors. Diagnosing brain tumors using MRI imaging is a difficult task due to the structure of the brain. MRI imaging provides better results than CT scans, ultrasound, and X-rays because it is the most advanced medical technology that uses powerful magnets to create beautiful images of every part of the body. These MRI images can be processed and the image processing process can be used to create a detection system that uses various algorithms to detect brain tumors, as manual detection of tumors from MRI images will lead to human error. In this work plan, we use open-source data [1] and the priority will be to improve the existing image or create a better tumor detection process.

1.2 Literature Study

Liu Yuhan introduced the general analysis method of CNN in his article in 2018 [2]. Thanks to their local connections and weight sharing, CNNs can scan images and extract objects at a lower cost. Additionally, clustering increases the robustness of the network to spatial variance. However, the extracted features are often vague and difficult to interpret, and CNN serves as an end-to-end model in the image recognition process. The biggest challenge for the future conception of CNN is to provide a more stable operating environment and make numbers faster. Improvements in both hardware and software will help solve this problem.

Rajesh C. Patil and Dr A.S. Bhalachandra published a paper in 2012[3] which refers to the brain tumor segmentation from MR images .Here Pre-processing of images is done to remove noise and image enhancement .They proposed a better method for image segmentation .

In 2021, Muhammad Assam, H. Kanwal, U. Farooq, S. K. Shah, A. Mehmood, and G. S. Choi[4] presented a revolutionary technique that uses both individual and hybrid classifiers to identify MRI brain pictures as abnormal or normal. In the last stage of the model's classification process, the method used two hybrid classifiers: Random Subspace with Random Forest (RSwithRF) and Random Subspace with Bayesian Network (RSwithBN). The single classifier used in this approach was called Feed Forward - Artificial Neural Network (FF-ANN).

Zhengchao Dong, Lenan Wu, Yudong Zhang and Shuihua Wang (2011)[5] introduced a novel approach for classifying T2-weighted brain MRI images, comprising three stages. Initially, 1024 features were extracted from each image using Discrete Wavelet Transform (DWT). Subsequently, Principal Component Analysis (PCA) was applied in the second stage to reduce these features to 19. Finally, the reduced set of 19 features was fed into an Artificial Neural Network (ANN) classifier in the third stage for classification. The method demonstrated promising results in terms of accuracy.

A method to distinguish between photos that are healthy and those that are impacted by diseases including Alzheimer's, cancer, and glioma was presented in 2011 by S. Lahmiri and M. Boukadoum [8]. The method required extracting the best features from the sub-bands LH and HL using the Discrete Wavelet Transform (DWT). Following the decomposition of brain MRI images, features were retrieved in both horizontal and vertical orientations. To improve accuracy and efficiency in classification, three classifiers—Probabilistic Neural Network (PNN), K-Nearest Neighbors (KNN), and Learning Vector Quantization (LVQ)—were combined into a single Support Vector Machine (SVM). Promising results were obtained when the technique was validated using a dataset from Harvard Medical College.

In 2014, H. B. Nandpuru, S. S. Salankar, and V. R. Bora proposed an automated technique for distinguishing between affected and healthy MRI images. They employed a Median filter to eliminate salt-and-pepper noise and unwanted components[9] like scalp and skull, thereby enhancing image quality by noise reduction. Four types of features were extracted, including power law transformation, texture, symmetrical, and grayscale features. Principal Component Analysis was then applied to optimize these features set, which were subsequently classified using Support Vector Machines (SVM) in the classification phase. The assessment included Linear Kernels (LKs), Quadratic Kernels (QKs), and Polynomial Kernels (PKs), achieving accuracies of 74%, 84%, and 76%, respectively.

Hussein Ibrahim, Abdelrehman Ahmed, and Yusra Ibrahim Mohamed published a paper in 2013 proposing neural network technology for magnetic resonance imaging human brain image classification [10]. The three stages of the suggested neural network technology are classification, dimensionality reduction, and preprocessing. During the final phase, an MRI brain image was classified as normal or abnormal using a Back-Propagation Neural Network classifier. This model's accuracy was 96.33%.

A new automatic diagnosis technique based on MRI image classification was proposed in 2011 by N.H. Rajini and R. Bhavan [11]. In the first step, we used the discrete wavelet transform

(DWT) to extract features from MR images. Each classifier in the classification stage is two. Feed-forward back-propagation artificial neural networks (FP-ANN) form the basis of the first classifier, while k-nearest neighbors (k-NN) form the basis of the second. FP-ANN and k-NN have 90% and 99% accuracy rates, respectively.

Kalbhani et al.[12] proposed a three-stage method to classify normal and abnormal brain MRI images. In the first stage, two-dimensional discrete wavelet transform was used for feature extraction. The proposed paper used the multi-cluster selection process to choose the best and most effective features. He whittled the initial run down to 41 and then sent it to the next stage for classification stage. The researchers used multiple feature sets and KNNs to classify healthy images as well as images containing injury and disease. Classification accuracy is high compared to others state of art techniques.

Bhausaheb Shinde, Dnyandeo Mhaske, and AR Dani published a paper on detecting and removing noise in MRI images in 2012 [15]. Salt and pepper noise can be detected and removed from medical images by using various filtering techniques such as median filtering, adaptive filtering and median filtering. The results are analyzed, compared to noise samples, and evaluated with qualitative measurements such as mean and standard deviation.

M.F.B. Osman, N.B. Abdullah and N.F.B. Kamal used SVM to distinguish normal and abnormal MRI images in their 2011 paper [16]. Proposed methods include accessing a brain MRI dataset using wavelet-based feature extraction and then using SVM for classification. The images in the image set contain T2 technical weight images with a resolution of 256×256 pixels each. A total of 32 images were considered in this task, of which 22 were normal and 10 were abnormal(containing diseases). After the images are processed, the images are sent to the SVM classifier for classification.

A CNN architecture for brain tumor classification was proposed by Milica M. Badža and Marko Č. Barjaktarović in 2020 [18]. Three different tumor kinds' T1-weighted, contrast-enhanced MRI images were used to conduct the classification. Record-wise and subject-wise 10-fold cross-validation was performed on the original and supplemented picture databases in order to assess the network. An input layer, two main blocks, a classification block, and an output layer make up the network design.

1.3 Problem Statement

Today, we see that most tumors are life-threatening, and brain tumors are one of them. It is known that brain tumors can have many kinds of shapes, sizes, locations and uses, which makes the investigation and diagnosis of tumors very difficult. Identification of tumors from MRI images is important and will vary depending on the specialist and other factors such as lack of specificity and whether MRI images are evaluated for identification as brain tumors or non-brain tumors. Therefore, automatic identification of brain tumors from MRI images could help solve serious problems and provide better outcomes. Detecting brain tumors from the patient's various symptoms has been a major challenge for doctors and nurses in diagnosis and treatment planning. In fact, some tests can take a lot of time, work, and make it difficult for doctors to make an accurate cancer diagnosis.

1.4 Motivation

As medical practitioners and pathologists face various challenges in detecting tumors manually from MRI images, there is a need for an automatic detection process. Thus, the main aim of the proposed work is to design a machine learning model for automatic detection of tumors to obtain more accuracy from the imaging dataset, which plays a vital role in the diagnosis of tumors. This model will hopefully help pathologists to reduce their workload and minimize human error while maintaining and improving the accuracy of tumor detection.

CHAPTER 2

METHODOLOGY

2.1 Introduction

Detecting and classifying tumors from MRI images is a difficult task due to the structure of the brain. Several stages of image classification include preprocessing (enhancement) of MRI images, feature extraction, and final classification.

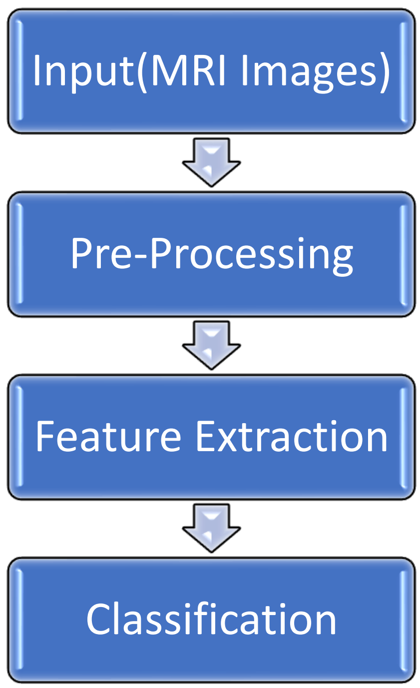

Figure 2.1 Steps for the method

Python programming language was used in the experiment, and a Jupyter Notebook IDE was used to run the output of a brain tumor. Four crucial stages of image processing have been implemented here: feature extraction, classification, segmentation of the questionable section, and pre-processing of MRI images.

2.2 About dataset

The datasets that have been used was taken from Kaggle website . The dataset comprises of 7023 MRI images each with a resolution of 512 X 512 categorized as :

a. Glioma
b. Meningioma
c. no tumor
d. pituitary

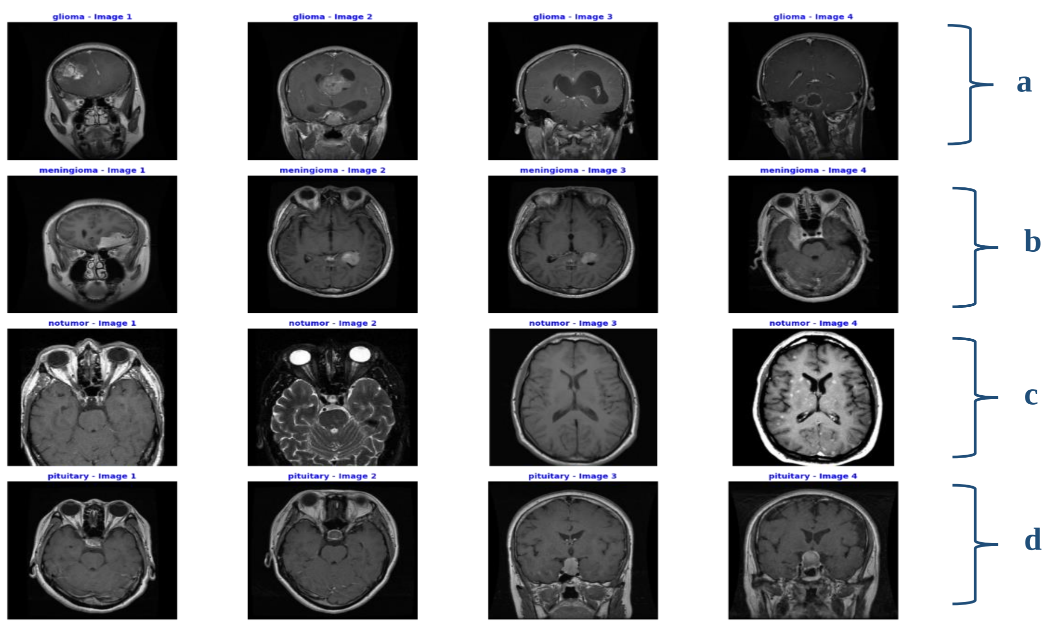

Figure 2.2 MRI images of brain

a. Glioma
b. Meningioma
c. No tumor
d. pituitary

Let know about each of the categories in detail .

a. Glioma

Glioma represents a type of tumor originating in the brain or spinal cord, arising from glial cells, which provide support and insulation for neurons. Gliomas manifest with a wide spectrum of aggressiveness, ranging from slow-growing benign tumors to fast-growing malignant ones. MRI images depicting gliomas typically reveal abnormal tissue within the brain or spinal cord, often appearing as irregular masses or lesions with distinct boundaries. Surrounding edema and mass effect are common features observed in glioma MRI images, signifying fluid accumulation and tissue displacement caused by tumor growth.

b. Meningioma

Meningioma is a category of tumor arising from the meninges—the protective layers surrounding the brain and spinal cord. These tumors are often slow-growing and benign, though they can occasionally become malignant. Meningioma MRI images typically depict a characteristic dural attachment, where the tumor originates from the outer layer of the meninges. Enhancement patterns indicative of increased vascularity within the tumor may be observed on MRI scans. Some meningiomas may exhibit calcifications or hyperostosis on MRI scans, providing additional diagnostic clues.

c. No Tumor

MRI images categorized as "no tumor" indicate the absence of detectable abnormal tissue or lesions within the brain or spinal cord. These images depict the normal anatomical structures of the brain and spinal cord without evidence of pathology. Normal structures within the brain and spinal cord exhibit symmetrical distribution and morphology, with clear ventricles and sulci. Unlike images depicting tumors, "no tumor" MRI images do not display enhancement patterns indicative of increased vascularity or abnormal tissue growth. These images serve as reference or control images for comparison with images depicting pathological conditions such as tumors.

d. Pituitary

Pituitary MRI images focus specifically on the pituitary gland, a small gland located at the base of the brain that plays a crucial role in hormone regulation. These images depict the size, shape, and structure of the pituitary gland, which should appear as a well-defined structure with uniform signal intensity. Pituitary adenomas, the most common type of pituitary tumor, may be visualized as focal lesions within the gland. Pituitary MRI imaging may also involve hormonal evaluation to assess pituitary function, aiding in the diagnosis of conditions such as hypopituitarism or hyperpituitarism.

2.3 Pre-processing

Although MRI can produce good images, the images contain unwanted objects such as the scalp and skull, and noise may occur due to the operator's lack of attention. To increase the accuracy of the application process, the image must be not only clear, but also free from unnecessary objects and noise. During the preparation process, the image is first cropped to remove excess edges in the image, and then, in the preliminary stage, a median filter[4] is used to remove salt and pepper noise as well as the scalp and skull without affecting the limbic brain MR images. At this stage, the given image is also converted from a grayscale image to a color data (RGB) image. Due to its small size, this function uses a 3×3 mask to speed up calculation time. After the first stage is completed, the resulting image is cleared of unwanted objects and noise and converted into a color (RGB) image. The reason for this transformation is that the image in color (RGB) form contains richer information than the gray image. Figures 2.3(a) and 2.3(b) first show the finished image.

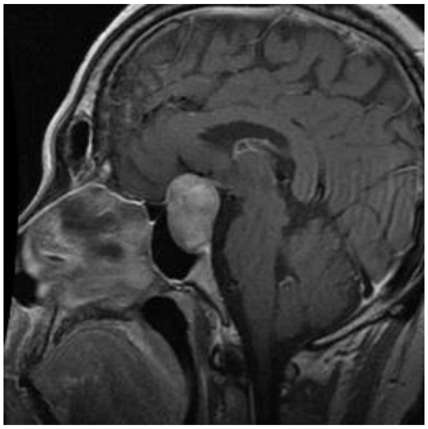

Figure 2.3(a) Image Before pre-processing

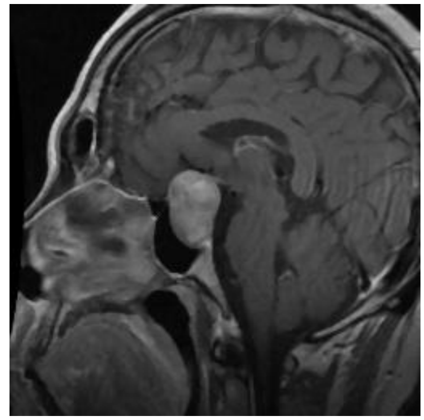

Figure 2.3(b) Image After pre-processing

2.4 Feature Extration

Feature extraction is a fundamental step in machine learning, especially in computer vision tasks involving image data. It involves transforming raw input data into a more compact and meaningful representation that captures important visual patterns and characteristics. In this work done, we have used the feature extraction process using a pre-trained VGG16 convolutional neural network (CNN) model[17][19].

VGG16 is a deep convolutional neural network architecture that has been pre-trained on the large-scale ImageNet[21] dataset. It is made of 16 layers, namely convolutional layers, many pooling layers, and fully connected layers. The model is effective for various computer vision tasks, thanks to its ability to learn hierarchical representations of visual features.

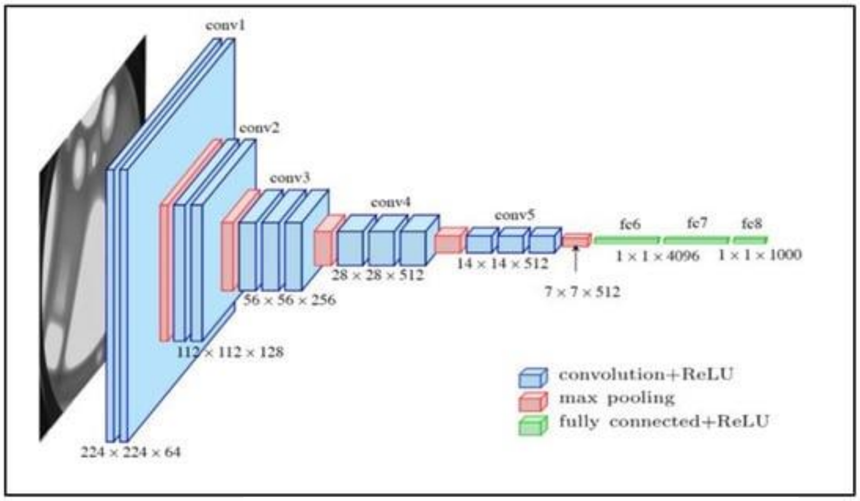

Figure 2.4 VGG-16 CNN Model

The feature extraction process involves utilizing the convolutional base of the pre-trained VGG16 model to extract high-level features from the input images. Specifically, we remove the fully connected layers (i.e. top layers) of the VGG16 model and retain only the convolutional layers. This convolutional base serves as a feature extractor, capturing hierarchical representations of visual patterns learned during the model's training on the ImageNet dataset. It also helps in getting more information from the input images.

This process of extracting feature from pre-trained models is called as transfer learning . Transfer learning (TL)[22] is a great strategy for training new models on small datasets. In this method, the network is first trained on large datasets (e.g., ImageNet) and then the learned features are reused and applied to small-paper tasks. The ImageNet database[23] contains large number (in millions) of images and nearly hundreds of annotation classes. It is designed to facilitate the training of Deep Learning models focusing on image classification, object location and object detection[23]. used. These models come with extensive training that makes them easy to reuse on similar problems. It is therefore possible to take advantage of the state-of-the-art model to, for example, reuse architectures recently released by the scientific community, replacing the study of general properties with other purposes, such as medical imaging deployment.

During implementation, we load the pre-trained VGG16 model using TensorFlow's Keras API. After that the layers of the model was freezed to prevent them from being trained during feature extraction. Next, we pass the preprocessed images through the convolutional base of the VGG16 model and extract the activations of the last convolutional layer. These activations serve as the extracted features, representing the visual characteristics of the input images. The output of the feature extraction process is a set of feature vectors for each input image. Each feature vector contains a compact representation of the image's visual content, capturing important patterns such as edges, textures, and object shapes. These features can be considered as high-level abstractions of the original image data, suitable for input to subsequent machine learning models or analysis tasks.

2.5 Classification

After completing the feature extraction process using the pre-trained VGG16 model, the subsequent step involves the classification of images based on these extracted features. The classification process encompasses several key steps aimed at training a custom classifier to accurately predict the labels or categories of the input images.

To begin with, the feature extraction process entails passing the preprocessed images through the convolutional base of the VGG16 model. This process allows us to capture important visual patterns and characteristics present in the input images. After that a custom classifier is designed to learn the mapping between the extracted features and the corresponding labels. In the provided code, a simple fully connected neural network architecture is used as the custom classifier. This classifier typically consists of one or more dense (fully connected) layers followed by an output layer with Softmax activation for multi-class classification tasks. The custom classifier is responsible for learning the intricate relationships between the input features and their associated labels.

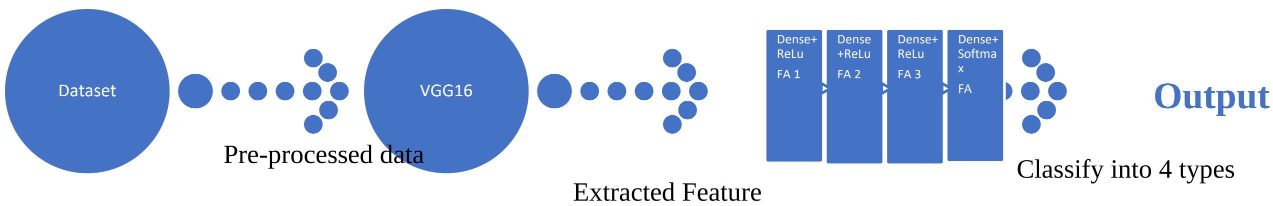

Figure 2.5 Flow of the proposed mechanism

In the classification process following feature extraction, the custom classifier is a neural network designed to map the extracted features to their corresponding labels. In this implementation, the custom classifier comprises several layers:

1. Rescaling Layer

At the outset of the custom classifier architecture, the input images undergo rescaling through the Rescaling layer. This crucial preprocessing step ensures that pixel values are normalized to fall within the range [0, 1]. By rescaling the pixel values, we standardize the input data and mitigate the impact of varying pixel intensity ranges across different images. Normalizing the input data enhances model stability and convergence during training, ultimately facilitating more robust and reliable predictions.

2. Flattening and Dense Layers

Following the Rescaling layer, the flattened representation of the extracted features serves as the input to a series of dense layers. The Flattening layer reshapes the extracted features into a one-dimensional array, enabling seamless integration with the subsequent dense layers. These dense layers, equipped with rectified linear unit (ReLU) activation functions, facilitate the model's capacity to learn intricate patterns and relationships within the feature space. By employing multiple dense layers, the custom classifier gains the flexibility to capture complex nonlinear mappings between the input features and the target labels.

3. Dropout Regularization

Incorporating dropout regularization within the custom classifier architecture is essential for combating overfitting—a common challenge in deep learning models. Dropout layers are strategically inserted between dense layers to prevent individual neurons from becoming overly reliant on specific features during training. By randomly deactivating a fraction of neurons during each training iteration, dropout regularization encourages the model to develop more robust and generalizable representations of the input data. In the proposed architecture, we employ dropout layers with dropout rates of 0.7 and 0.5, effectively encouraging diversity in feature utilization and promoting model generalization.

4. Output Layer

At the culmination of the custom classifier architecture lies the output layer—a critical component responsible for generating predictions based on the learned features. As the classification task involves multi-class prediction, the output layer is outfitted with a softmax activation function. This activation function computes the probability distribution across all possible classes, enabling the model to assign a likelihood to each class label. With a number of neurons equal to the total number of classes in the dataset, the output layer produces a probability vector encapsulating the model's confidence in each class prediction.

CHAPTER 3

RESULTS AND DISCUSSION

In the study ,to implement and test the proposed system , a Core i5 system with a 2.4GHz processor and 16GB RAM was used. The system runs the 64-bit Windows 11 operating system. Tools used in testing include Keras, TensorFlow, Jupyter Notebook, scikit-learn, etc. takes place.

This study examines the proposed system using different methods and compares the results with existing studies. It is known from the literature that most researchers use accuracy to judge the performance of the methods. This model was trained over 20 epochs to get the given accuracy . The accuracy recorded for the model was **94.66%.** This metric signifies the proportion of correctly classified MRI images from the validation set. A high validation accuracy indicates the model's proficiency in distinguishing between the different classes of MRI images, including Glioma, Meningioma, No Tumor, and Pituitary. The loss value recorded was **21%** which signifies that the model's predictions closely align with the actual labels, indicating a high degree of confidence in the model's classifications. Figure 3.1 illustrates the loss curve of training and validation.

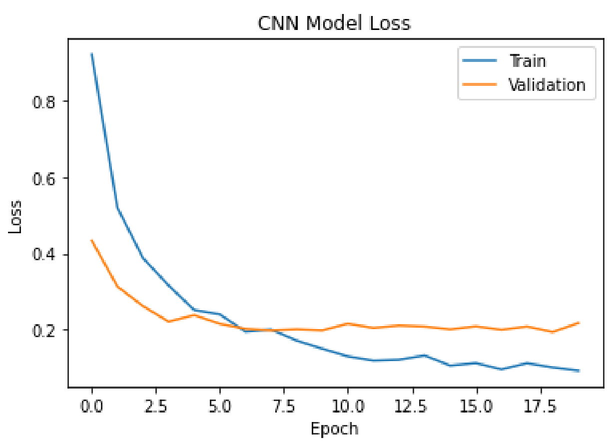

Figure 3.1 Loss curve of training and validation

Loss Curve :

The loss curve provides valuable insights into the training dynamics and performance of the MRI image classification model. By visualizing the evolution of the training and validation losses over epochs, we gain a deeper understanding of how the model learns and generalizes to unseen data.

Interpreting the Loss Curve:

In the (see Figure 3.1), the loss curve depicted a clear trajectory of the model's optimization process. The training loss, representing the error incurred on the training data during each epoch, steadily decreased as the model learned to better fit the training data. Simultaneously, the validation loss, reflecting the model's performance on a separate validation dataset, exhibited a similar downward trend, indicating generalization to unseen data.

Confusion matrix :

In essence, the confusion matrix provides us with an understanding of the performance of the suggested classifier in terms of individual-on-individual class performance. Therefore, a test set whose real labels are known is usually used to fill out a confusion matrix. After the classifier processes the test data, predictions are recorded. Next, a table showing the true and anticipated labels is completed. Lighter-colored boxes predict the class incorrectly, while blue-colored boxes accurately indicate the class.

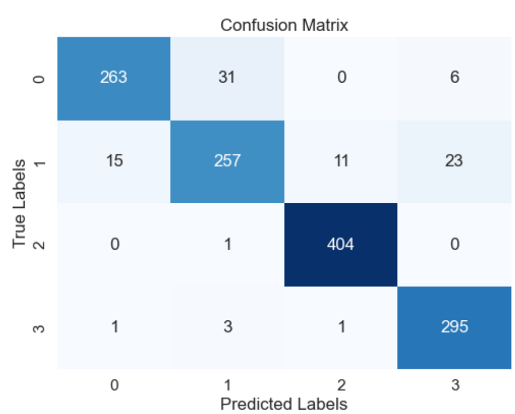

Figure 3.2 Confusion Matrix

CONCLUSION

MRI images are best suitable for brain tumor detection. In this study Digital Imaging Processing Techniques are important for brain tumor detection by MRI images. The suggested method used median filter in the pre-processing stage. After pre-processing of images ,VGG16 model is used to extract the feature from the dataset and classification is done by fully connected layers where the model had obtained 94.66% of accuracy when run on a dataset of 4569 images in classifying three tumor categories and non tumor images. Its high accuracy and low loss metrics signify its potential clinical utility for assisting healthcare professionals in diagnosis and treatment planning. This work help in detection of tumor which in turn save the precious time of doctor and pathologist to diagnose the tumor automatically in short span of time.

FUTURE WORK

In the work done ,all the steps of image processing was successfully implemented that is pre-processing, feature extraction and classification using custom classifier that was explained in the methodology. As 94.66% of accuracy was achieved in the propsed model, for future it will be better try to implement different algorithm using more MRI images to get better accuracy result. This work could be expanded to employ various feature reduction techniques while minimizing execution time. It would be intriguing to contrast the outcomes of the suggested strategy with deep learning-based approaches.

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