A project report on

BRAIN TUMOR DETECTION AND CLASSIFICATION USING IMAGE PROCESSING AND MACHINE LEARNING

submitted in partial fulfillment of the requirements for
the award of the degree of

B.Tech

in

Electrical Engineering

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June, 2024

BONAFIDE CERTIFICATE

This is to certify that the project titled **BRAIN TUMOR DETECTION AND CLASSIFICATION USING IMAGE PROCESSING AND MACHINE LEARNING** is a bonafide record of the work done by

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ABSTRACT

Nowadays, tumors stand as the second leading cause of cancer, posing a significant threat to numerous individuals. The medical field urgently requires swift, automated, efficient, and dependable techniques for tumor detection, especially in cases like brain tumors, where early detection is pivotal for effective treatment. The field of automated anomaly detection in medical imaging has rapidly evolved, particularly in diagnosing various medical conditions using Magnetic Resonance Imaging (MRI). Detecting tumors in MRI scans is crucial for treatment planning. The conventional method of detecting defect anomaly in MRI brain images was human inspection, but its practicality decreased with growing datasets. To overcome this, automated tumor detection methods emerged, aiming to save radiologists' time. However, due to the complexity of tumors, MRI brain tumor detection remains challenging. In this project, machine learning algorithms are employed to detect and classify brain tumors in MRI images. Techniques like the VGG16 CNN model, Support Vector Classifier, and K Nearest Neighbors are compared. The findings conclude that CNN model has the highest accuracy and can be used as a superior tool for analyzing and classifying brain tumors.

***Keywords* : MRI, kNN, SVC, SVM, VGG16, CNN, meningioma, glioma, pituitary, notumor**

ACKNOWLEDGEMENTS

We would like to express our deepest gratitude to the following people for guiding us through this course and without whom this project and the results achieved from it would not have reached completion.

Dr. Amrita Ganguly, Assistant Professor, Department of Electrical Engineering, for helping us and guiding us in the course of this project. Without her guidance, we would not have been able to successfully complete this project. Her patience and genial attitude is and always will be a source of inspiration to us.

Dr. Runumi Sarma, the Head of the Department, Department of Electrical Engineering, for allowing us to avail the facilities at the department.

We are also thankful to the faculty and staff members of the Department of Electrical Engineering, our individual parents and our friends for their constant support and help.

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CHAPTER 1
INTRODUCTION

1.1 Brain Tumor Detection System

Automated anomaly detection in medical imaging, especially MRI scans, is rapidly advancing and crucial for diagnosing various medical conditions, including brain tumors. The traditional manual inspection of MRI images is no longer practical due to the increasing data volume. To address this, automated tumor detection methods, particularly CNN models, have been developed, exhibiting superior accuracy. Brain tumors are critical health concerns requiring early detection for effective treatment. A computer-based system, utilizing advanced techniques like Convolutional Neural Networks, is designed to enhance brain tumor detection and classification in MRI images.

This system utilizes image processing nethods like segmentation and feature extraction to improve accuracy. By combining these methods, it simplifies the diagnostic process, ensuring quicker and more precise identification of brain abnormalities, potentially saving lives through early detection. The human body contains numerous organs, with the brain being the most critical. Brain dysfunction, often caused by issues like tumors, poses significant health challenges. Tumors result from uncontrolled cell growth, especially in the brain, consuming vital nutrients meant for healthy tissues, potentially leading to organ failure. Currently, manual examination of MR images is the standard practice for locating and assessing brain abnormalities like tumors. However, this method can be prone to inaccuracies and is time-consuming. Brain cancer, a severe ailment with a high mortality rate, necessitates early detection for effective intervention. To address this, a specialized system using computer-based procedures has been developed for early tumor detection and classification.

This system utilizes advanced techniques, including Convolutional Neural Networks, to analyze MRI images from different patients. Various image processing methods, such as segmentation, enhancement, and feature extraction, play crucial roles in identifying and characterizing tumors in MRI scans of cancer-affected patients. The process involves four key stages: Image Pre-Processing, Image Segmentation, Feature Extraction, and Classification, all aimed at enhancing the precision and efficiency of brain tumor detection. The integration of image processing and neural network techniques enhances the overall performance of detecting and classifying brain tumors in MRI images. This innovative approach not only streamlines the diagnostic process but also promises more accurate and timely identification of brain abnormalities, potentially saving lives through early intervention.

1.2 Overview of Brain and Brain Tumor

The brain, located within the protective enclosure of the skull, functions as the main control center of the nervous system. It's a vital organ that coordinates and regulates activities throughout the body. This organ helps us adapt to different situations, empowering us to deal with various environmental changes. Apart from its physical role, the brain processes thoughts and feelings, connecting people through actions and shared experiences. Its thinking abilities help us face and conquer many challenges. Essentially, the brain is where consciousness resides, blending sensory input, movement, and emotions seamlessly. It's like the conductor of our existence, blending the physical and mental aspects of life with finesse.

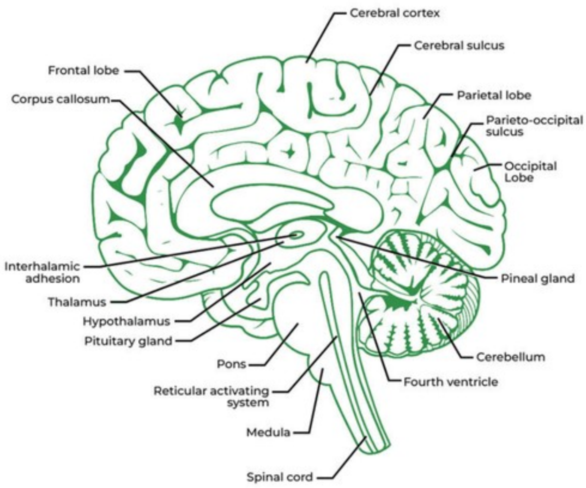

Figure 1.1: Structure of a brain

The brain, a complex and vital organ in the human body, is responsible for controlling various functions, including cognition, movement, and sensory perception. Comprising different regions, each with specific roles, the brain coordinates and regulates the body's activities. However, the occurrence of brain tumors can disrupt these functions.

1.2.1 Glioma Tumor

Gliomas are a type of tumor that originates in the glial cells, which provide support and protection to nerve cells in the brain. These tumors can vary in aggressiveness, with glioblastoma multiforme being one of the most malignant forms. Gliomas often infiltrate surrounding brain tissue, making complete surgical removal challenging.

1.2.2 Meningioma Tumor

Meningiomas arise from the meninges, the layers of tissue covering the brain and spinal cord. These tumors are typically slow-growing and often benign, although they can cause symptoms by pressing on surrounding structures. Meningiomas are more common in women and are often discovered incidentally during imaging studies.

1.2.3 Piyuitary Tumor

Pituitary tumors develop in the pituitary gland, a small gland at the base of the brain that regulates hormone production. These tumors can be noncancerous (benign) or, rarely, cancerous (malignant). Pituitary tumors may lead to hormonal imbalances, affecting various bodily functions. Due to the gland's location, surgical intervention is often performed through the nasal cavity.

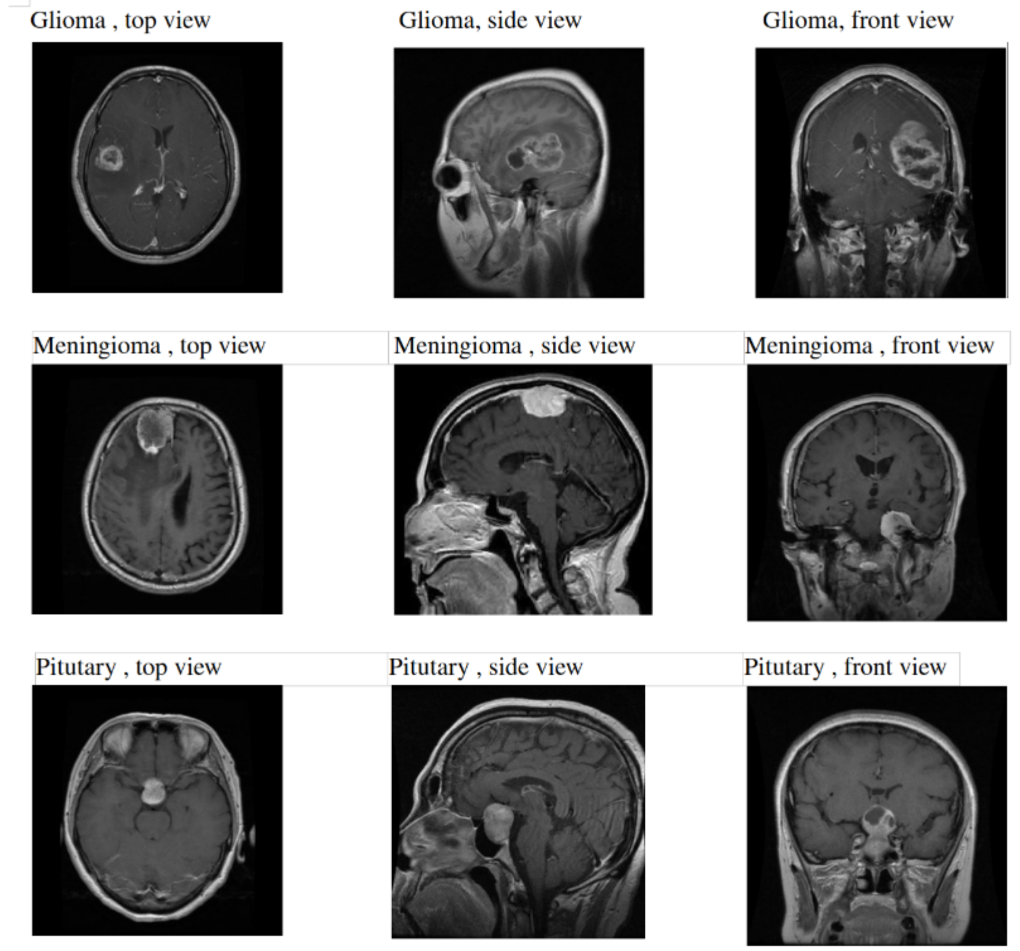

Figure 1.2: MRI image samples from the dataset

1.3 Objective

The objective of the brain tumor detection system project is to develop user friendly software that empowers doctors to accurately identify tumors and their causes, ultimately saving valuable time for patients. By offering a solution that is accessible and efficient, the system aims to detect tumors at early stages, enabling timely intervention and consultation.

By doing so, the project seeks to improve patient outcomes by facilitating prompt diagnosis and treatment, enhancing the overall quality of care for individuals affected by brain tumor.

1.4 Motivation

The primary motivation behind the the Brain tumor detection project goes beyond just identifying tumors. It's about understanding different types of tumors and doing detailed analysis. This is really important when doctors need to be sure if a tumor is present or not for the right diagnosis and treatment plan. The project is carefully set up to achieve this using a computer based system and advanced machine learning techniques. It looks for tumor blocks and then categorizes them using special algorithms called Convolutional Neural Networks. These algorithms analyze MRI images from lots of different patients. This thorough approach helps in spotting tumors accurately and classifying them correctly for better medical assessments. The project aims to enhance the diagnostic accuracy and efficiency of brain tumor detection, ultimately improving patient outcomes and medical decision-making processes.

1.5 Organization of the Report

Chapter 1 introduces Brain tumor Detection and Classification using Machine Learning, discussing its applications, system objectives, and motivation. It highlights the need for accurate methods to detect and classify brain tumors, emphasizing the role of machine learning in improving medical imaging.

A literature survey has been presented in second chapter which summarizes existing research in the field, offering insights into methodologies and findings related to Brain tumor Detection and Classification using Machine Learning. It serves as a reference for understanding the current state-of-the-art and identifying areas for further exploration.

Chapter 3 outlines the complete methodology, from MRI image acquisition to preprocessing, segmentation, and feature extraction. This chapter provides a detailed explanation of the techniques involved in detecting and classifying brain tumors, forming the basis for subsequent analysis and discussion.

The structure of the CNN model and process of implementing and training the VGG16 model have been described in chapter 4.

In Chapters 5 and 6, the introduction and implementation of Support Vector Classifier (SVC) and K Nearest Neighbors (KNN) algorithms have been discussed followed by the results obtained from their application.

Chapter 7 provides a comparative analysis of the VGG16 model, Support Vector Classifier (SVC), and K Nearest Neighbors (KNN), evaluating their performance and effectiveness.

Finally, Chapter 8 offers a comprehensive conclusion identifying the top- performing model based on its superior accuracy, thus summarizing the findings and insights presented throughout the report.

CHAPTER 2
LITERATURE REVIEW

Brain tumors represent a significant medical challenge due to their complexity and potential severity. Advancements in medical imaging, particularly Magnetic Resonance Imaging (MRI), have opened new avenues for early detection and accurate diagnosis. Machine learning, especially deep learning techniques like Convolutional Neural Networks (CNNs), has become instrumental in automating the classification of brain tumors, enhancing diagnostic accuracy and treatment planning. This literature review explores various studies that leverage CNNs and other machine learning approaches to classify and diagnose brain tumors from MRI data.

Toqa A. Sadoon, et al. in [1] discussed and examined MRI-based brain tumor classification using CNNs, focusing on glioma, meningioma, and pituitary tumors. The study, utilizing a dataset of 233 patients, highlights the superior performance of the proposed model, achieving notable accuracy metrics. Discussions include the impact of data preprocessing and augmentation on outcomes.

Wagh et al. in their study [2] introduced BrainNet, a novel CNN tailored for multiclass tumor classification, surpassing the performance of pre-trained transfer learning models like VGG13, VGG16, VGG19, Squeeznet, and InceptionResV2, trained on the acquired dataset.

In order to detect malignancies in brain MRIs, **Sharma et al.** [3] suggested using machine learning approaches. The research suggestion comprises of three key steps: preprocessing brain MRI pictures, extracting texture features with a Grey Level Cooccurrence Matrix (GLCM), and categorising the outcomes with machine learning.

In recent times, significant research has been conducted in the field of automated brain tumor classification. **Das et al.** [4] introduced preprocessing methods as an initial stage preceding the classification process. Their approach involved operations like resizing, histogram equalization, and Gaussian filtering applied to the input data before feeding it into the Convolutional Neural Network (CNN).

Malarvizhi et al. on their study[5], focused on automatic brain tumor classification through preprocessing involving median filtering, thresholding, and K-means clustering, with features extracted via GLCM. The SVM classifier distinguishes between benign and malignant tumors, aiding early detection and containment of cancerous cells.

Again study [6] aims to aid in diagnosing objects in x-ray medical images by employing various filtering techniques such as Blur, Emboss, Gaussian, etc., as preprocessing steps before edge detection. The MMG method is utilized to clarify edge detection, resulting in increased diagnostic confidence and reduced hesitation in object diagnosis from medical images.

Srinivas et al. in their study [7] conducts a comparative performance analysis of transfer learning-based CNN-pretrained models (VGG-16, ResNet-50, and Inception-v3) for automatically predicting brain tumor cells. Using an MRI brain tumor images dataset comprising 233 images, the aim is to locate brain tumors with the VGG-16 pretrained CNN model. Evaluation focuses on accuracy, with VGG-16 showing significantly improved results in both training and validation accuracy rates.

Anjum et al. conducted a comparison between deep learning (DL) methods utilizing transfer learning and traditional machine learning (ML) techniques for brain tumor detection. Results indicate that DL methods, particularly those based on ResNet101 with transfer learning, exhibited superior performance, showing promise for prognosis and treatment planning.

CHAPTER 3
PROPOSED WORKFLOW

3.1 Overview of Work

Research highlights the urgent need for automated brain tumor detection to safeguard human health. This involves extracting features and using machine learning to categorize tumors in MRI images. The proposed methodology covers everything from image acquisition to model evaluation, ensuring a thorough and efficient process for brain tumor detection.

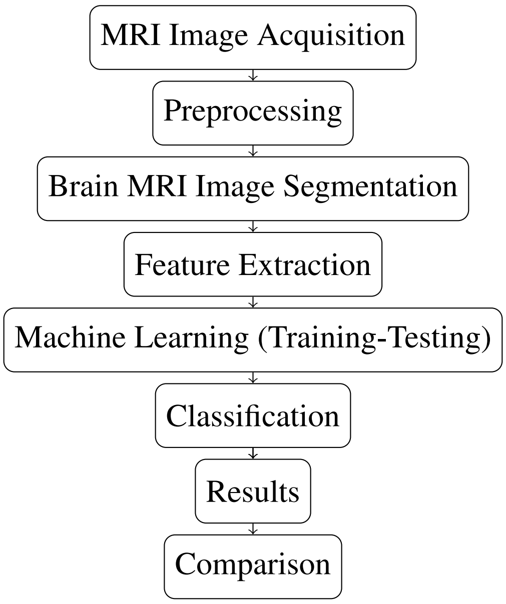

Figure 3.1: Proposed method for Brain Tumor Detection in MRI images

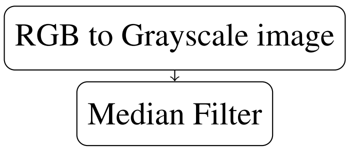

Figure 3.2: Proposed method for Preprocessing of MRI images

The methodology begins with gathering a diverse and representative dataset, which is crucial for training the model well. Then, images undergo preprocessing, where various transformations are applied to improve quality relevance of images. Following this, segmentation separates images into distinct regions based on pixel properties, making it easier for boundary identification essential for tumor detection.

Moving forward, feature extraction automatically finds important features in the images employing specialized algorithms . By eliminating the need for manual intervention, this stage enhances the efficiency of the entire process. After that, image classification predicts what objects are in the images based on predefined rules established during the training phase.

To make sure the methodology works well, models are evaluated using tools like confusion matrices and ROC (Receiver Operating Characteristic) curves. This helps understand each model's strengths and weaknesses and make better decisions for improving performance.

Overall, the method is carefully designed to include key steps, combining advanced image processing with thorough model evaluation to detect brain tumors effectively.

3.2 MRI Image Acquisition

The dataset has been acquired from kaggle.com website and it comprises of approximately 7,000 images. The training set was divided into two subgroups in the ratio 80:20. The dataset distribution is shown below:

Table 3.1: Dataset Distribution

Class	**Number of Images**	
	Training set images	***Testing set images***
Glioma	1316	298
Meningioma	1279	263
No-tumor	1449	372
Pituitary	1429	288
Total	**5473**	**1221**

3.3 Image Preprocessing

The primary objective of preprocessing the data is to enhance the quality of the images before subsequent processing stages. This involves eliminating any noise present in the images. The preprocessing steps employed include grayscale transformation, image resizing, and noise removal using a median filter. Grayscale transformation is instrumental in adjusting pixel intensities by mapping input gray levels to different output levels. Additionally, the median filter plays a crucial role in reducing salt and pepper noise, owing to its superior denoising capabilities. These preprocessing techniques collectively contribute to improving the overall quality and reliability of the data for subsequent analysis and interpretation.

3.4 Image Segmentation

Image segmentation, a fundamental process in image analysis, involves dividing an image into multiple segments to facilitate meaningful and useful analysis. In this context, the Otsu thresholding method emerges as a helpful segmentation technique. It's well-known for its effectiveness because it automatically finds the best threshold value based on the gray values in the image, without needing any input from the user.

The Otsu binarization method operates by estimating the threshold value based on the peaks identified in the histogram of the image. By discerning the approximate value situated between these peaks, the technique effectively selects the optimal threshold value. Often referred to as automatic threshold selection or region-based segmentation, Otsu's method maximizes the interclass variance to identify the threshold that maximizes the distinction between the foreground and background classes.

Otsu's method picks the threshold value that creates the biggest difference between foreground and background in the binary image. This makes it easier to separate objects from the background, leading to more accurate segmentation. It also helps make the segmented areas easier to understand. Overall, Otsu's method is a useful and efficient way to segment images, giving us important information about the structure and features of the images we're analyzing.

3.5 Feature Extraction

In the proposed VGG16 CNN model, various kernels are employed to serve as filters to extract intricate features from visual images. These kernels, essentially matrices, move across the input data and calculate dot product with sub-regions, resulting in a matrix of dot products as the output. CNNs use multiple filters per layer, allowing them to extract many features simultaneously, making the network better at recognizing complex patterns in the data.

Each layer's output from the filters goes through a non-linear activation function, like ReLU, which adds complexity to the learning process. This step helps the network learn more advanced features, important for understanding subtle details in the input images.

Among the filters used, the Sharpen filter is essential for enhancing high-frequency pixels and reducing low-frequency ones, making images clearer. Similarly, the Emboss filter brightens pixel values while darkening others to improve visual contrast.

Additionally, the Sobel filter is valuable for highlighting edges in images by calculating gradients in horizontal or vertical directions. Lastly, the condense function helps reduce the size of feature maps, making the computational process more efficient.

Figure 3.3: Different types of filters used

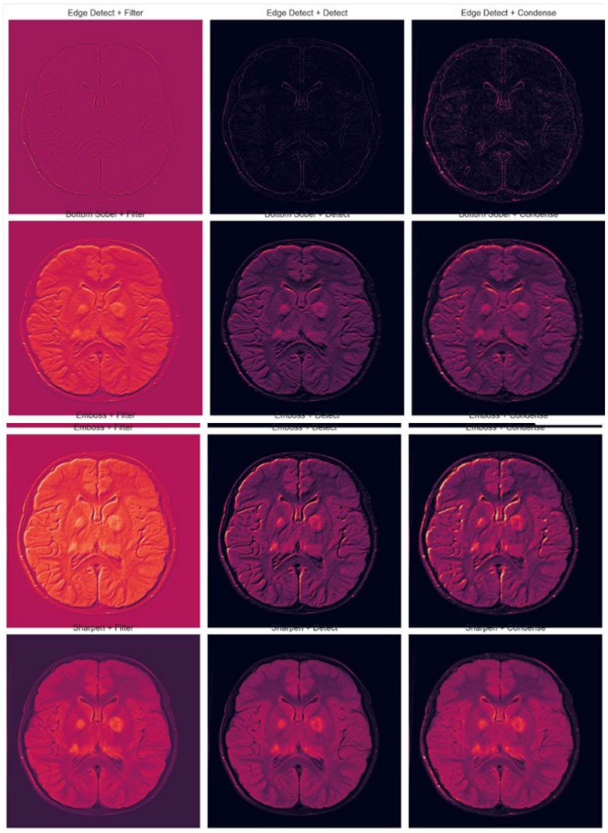

Figure 3.4: Application of Kernels in CNN

CHAPTER 4
CNN MODEL STRUCTURE AND IMPLEMENTATION OF VGG16 MODEL

4.1 CNN Model Structure

Convolutional Neural Networks (CNNs) are a powerful tool for machine learning, especially in tasks related to computer vision. Convolutional Neural Networks, or CNNs, are a specialized class of neural networks designed to effectively process grid-like data, such as images. A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The architecture of CNNs is inspired by the visual processing in the human brain, and they are well-suited for capturing hierarchical patterns and spatial dependencies within images. Key components of a Convolutional Neural Network include:

Convolutional Layers: These layers apply convolutional operations to input images, using filters (also known as kernels) to detect features such as edges, textures, and more complex patterns. Convolutional operations help preserve the spatial relationships between pixels.

Pooling Layers: Pooling layers downsample the spatial dimensions of the input, reducing the computational complexity and the number of parameters in the network. Max pooling is a common pooling operation, selecting the maximum value from a group of neighboring pixels.

Activation Functions: Non-linear activation functions, such as Rectified Linear Unit (ReLU), introduce non-linearity to the model, allowing it to learn more complex relationships in the data.

Fully Connected Layers: These layers are responsible for making predictions based on the high-level features learned by the previous layers. They connect every neuron in one layer to every neuron in the next layer.

CNNs are trained using a large dataset of labeled images, where the network learns to recognize patterns and features that are associated with specific objects or classes. Proven to be highly effective in image-related tasks, achieving state-of-the-art performance in various computer vision applications. Their ability to automatically learn hierarchical representations of features makes them well-suited for tasks where the spatial relationships and patterns in the data are crucial for accurate predictions. CNNs are widely used in areas such as image classification, object detection, facial recognition, and medical image analysis. The convolutional layers are the key component of a CNN, where filters are applied to the input image to extract features such as edges, textures, and shapes. The output of the convolutional layers is then passed through pooling layers, which are used to down-sample the feature maps, reducing the spatial dimensions while retaining the most important information. The output of the pooling layers is then passed through one or more fully connected layers, which are used to make a prediction or classify the image.

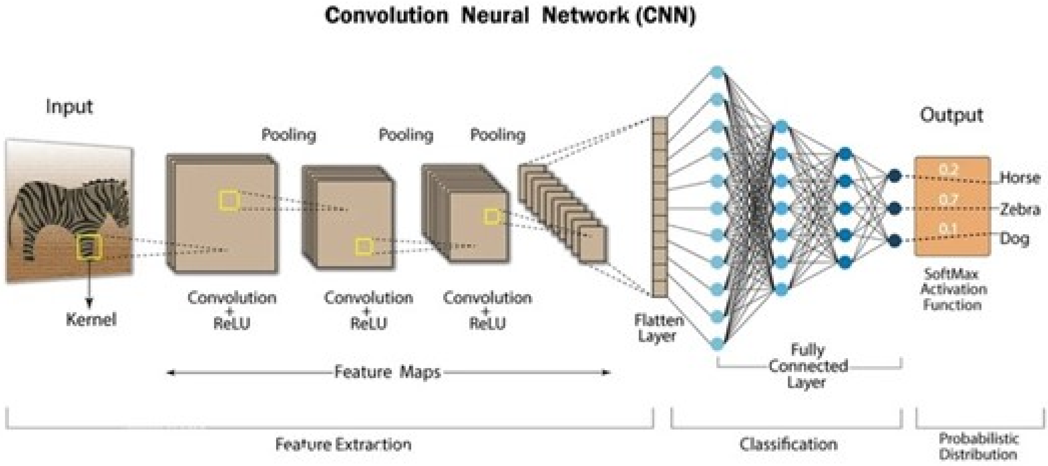

Figure 4.1: CNN Model Structure

4.2 Implementation of VGG16 Model

The VGG-16 model, named after the Visual Geometry Group at the University of Oxford where it was developed, represents a significant advancement in deep learning architectures, especially for image analysis tasks such as brain tumor detection in MRI images.

The VGG-16 architecture is characterized by its depth, comprising a total of 16 layers, including 13 convolutional layers and 3 fully connected layers. These layers are stacked sequentially, with each layer performing specific operations crucial for feature extraction, abstraction, and classification.

The 13 convolutional layers in VGG-16 utilize small filters (typically 3x3 or 1x1) to convolve over the input image. This process involves extracting features such as edges, textures, and shapes by performing convolution operations. The multiple convolutional layers are designed to capture increasingly complex and abstract features as information flows through the network. The primary role of the convolutional layers is feature extraction. By applying a series of convolution operations and activation functions (typically ReLU), the model can learn hierarchical representations of the input data. These representations encode important spatial patterns and local features, enabling the model to understand the underlying structures within the MRI images. Following the convolutional layers, VGG-16 includes 3 fully connected layers, also known as dense layers. These layers are responsible for performing classification based on the features extracted by the convolutional layers. The dense layers combine the learned features and make predictions regarding the presence or absence of brain tumors in the MRI images. The depth of the VGG-16 model, characterized by its numerous stacked layers, enables it to capture intricate details and complex relationships within the input images. This deep architecture is crucial for achieving high accuracy in tasks like brain tumor detection, as it allows the model to learn diverse and hierarchical representations of the data, leading to more robust and accurate predictions. Due to its deep architecture, effective feature extraction capabilities, and robust classification abilities, the VGG-16 model is known for achieving high accuracy in image classification tasks, including brain tumor detection. Its ability to learn intricate patterns and relationships within the MRI images contributes significantly to its success in accurately identifying and classifying brain tumors.

Overall, the VGG-16 model's architecture, combining multiple convolutional and fully connected layers, plays a pivotal role in enabling accurate and reliable detection of brain tumors in MRI images, making it a valuable tool in medical imaging analysis and diagnosis.

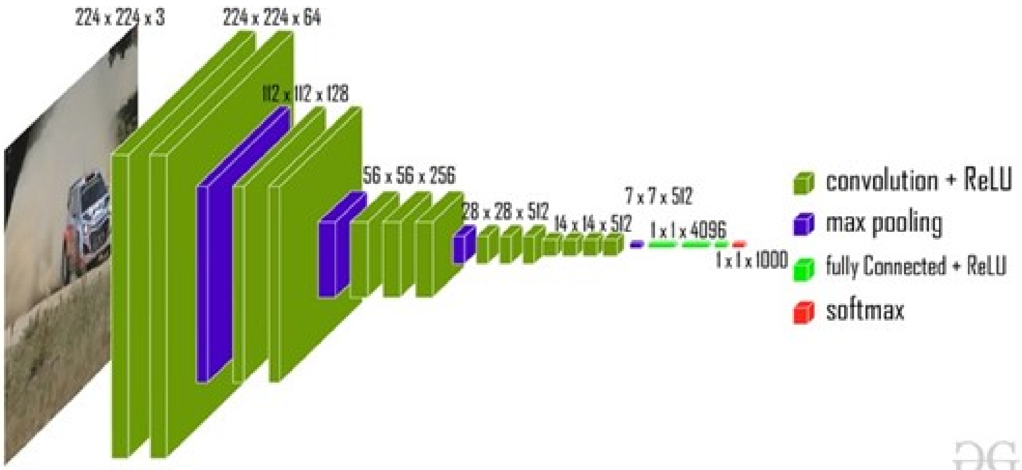

Figure 4.2: Working of VGG16 Model

Figure 4.3: Layers of VGG16 Model

Setting up the environment: The development environment is established by installing crucial libraries such as TensorFlow and Keras, renowned for their efficacy in deep learning tasks. These libraries furnish potent tools for crafting and training neural network models. Simultaneously, the MRI dataset containing brain tumor images is integrated into the environment, furnishing the requisite data for model training and assessment. Through the incorporation of TensorFlow and Keras, professionals and researchers in medical imaging can harness these robust libraries to create and implement sophisticated deep learning models. Moreover, the inclusion of the brain tumor MRI image dataset facilitates the exploration of its attributes, preprocessing methodologies, and subsequent analysis to achieve precise brain tumor detection. This union of a finely-tuned environment and relevant data forms the groundwork for conducting comprehensive research and driving advancements in brain tumor detection methodologies.

4.3 Training and results of VGG16 Model

During the training process of the model, several standard metrics such as accuracy, precision, and recall are used to evaluate its performance. The training occurs over multiple epochs, with each epoch representing a full pass through the training dataset. After each epoch, the model's performance on a separate validation set is assessed. This validation step is crucial as it helps in fine-tuning the model's hyperparameters and ensures that the model can generalize well to unseen data.

The training updates typically include monitoring the loss and accuracy values for each epoch. The loss value indicates how well the model is performing; a decreasing loss over epochs signifies that the model is learning and making more accurate predictions. On the other hand, accuracy values indicate the proportion of correctly classified images during both training and validation.

In a specific training session, achieving high accuracy on both the training and validation sets is a positive sign. It demonstrates the model's capability to effectively detect brain tumors in MRI images, showcasing its ability to generalize well and make accurate predictions on new, unseen images. This indicates the potential of the model to be deployed in real-world scenarios for accurately classifying brain tumors, which is crucial for medical diagnosis and treatment planning.

```
Epoch 1/10
218/218 [==============================] - 1069s 5s/step - loss: 0.4260 - sparse_categorical_accuracy: 0.8422
Epoch 2/10
218/218 [==============================] - 935s 4s/step - loss: 0.1991 - sparse_categorical_accuracy: 0.9271
Epoch 3/10
218/218 [==============================] - 915s 4s/step - loss: 0.1335 - sparse_categorical_accuracy: 0.9501
Epoch 4/10
218/218 [==============================] - 927s 4s/step - loss: 0.1030 - sparse_categorical_accuracy: 0.9616
Epoch 5/10
218/218 [==============================] - 915s 4s/step - loss: 0.0788 - sparse_categorical_accuracy: 0.9727
Epoch 6/10
218/218 [==============================] - 915s 4s/step - loss: 0.0624 - sparse_categorical_accuracy: 0.9778
Epoch 7/10
218/218 [==============================] - 908s 4s/step - loss: 0.0410 - sparse_categorical_accuracy: 0.9840
```

Figure 4.4: Traingin of VGG16 Model

	precision	recall	f1-score	support
glioma	0.97	0.97	0.97	298
meningioma	0.93	0.96	0.95	263
notumor	1.00	0.99	1.00	372
pituitary	0.99	0.97	0.98	288
accuracy			0.97	1221
macro avg	0.97	0.97	0.97	1221
weighted avg	0.97	0.97	0.97	1221

Figure 4.5: Result of VGG16 Model

CHAPTER 5
SUPPORT VECTOR CLASSIFIER KNN CLASSIFIER

In this study, we have studied two machine learning models: Support Vector Classifier (SVC) and K-Nearest Neighbors (KNN). Both models were implemented to classify brain tumor MRI images. After applying these models to the dataset, we performed a comparative analysis to evaluate the performance and accuracy of each model in classifying the MRI images. The results of this comparison provided insights into the effectiveness of SVC and KNN in the context of brain tumor diagnosis through MRI imaging.

5.1 Introduction

Support Vector Machine (SVM) is a powerful machine learning algorithm used for linear or nonlinear classification, regression, and even outlier detection tasks. SVMs can be used for a variety of tasks, such as text classification, image classification, spam detection, handwriting identification, gene expression analysis, face detection, and anomaly detection. SVMs are adaptable and efficient in a variety of applications because they can manage highdimensional data and nonlinear relationships.

SVM algorithms are very effective as we try to find the maximum separating hyperplane between the different classes available in the target feature.

Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression.The main objective of the SVM algorithm is to find the optimal hyperplane in an N-dimensional space that can separate the data points in different classes in the feature space. The hyperplane tries that the margin between the closest points of different classes should be as maximum as possible. The dimension of the hyperplane depends upon the number of features.

SVMs are commonly used within classification problems. They distinguish between two classes by finding the optimal hyperplane that maximizes the margin between the closest data points of opposite classes. The number of features in the input data determine if the hyperplane is a line in a 2-D space or a plane in a n-dimensional space. Since multiple hyperplanes can be found to differentiate classes, maximizing the margin between points enables the algorithm to find the best decision boundary between classes. This, in turn, enables it to generalize well to new data and make accurate classification predictions. The lines that are adjacent to the optimal hyperplane are known as support vectors as these vectors run through the data points that determine the maximal margin.

The SVM algorithm is widely used in machine learning as it can handle both linear and nonlinear classification tasks. However, when the data is not linearly separable, kernel functions are used to transform the data higher-dimensional space to enable linear separation.

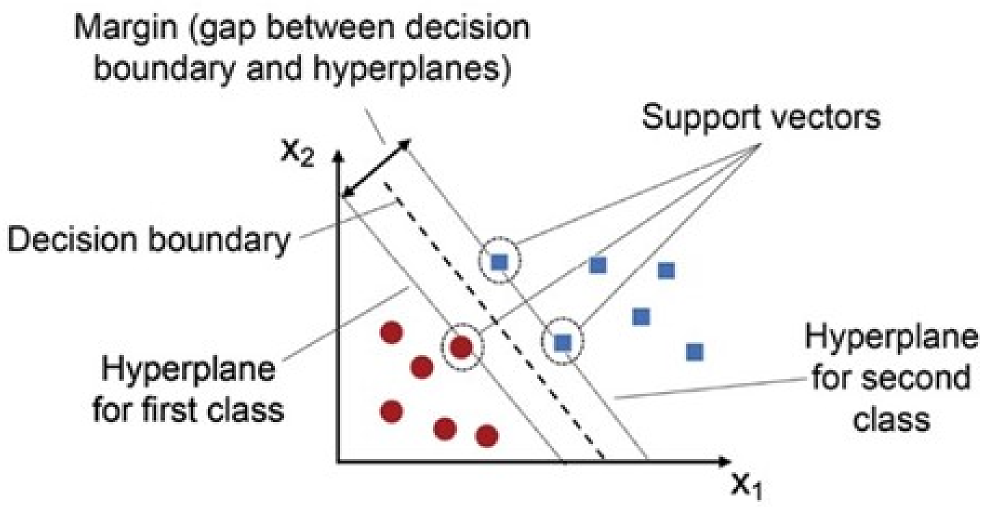

Figure 5.1: Hyperplane of SVC

The k-nearest neighbors (KNN) algorithm is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. It is one of the popular and simplest classification and regression classifiers used in machine learning today. K-Nearest Neighbors (KNN) is a lazy learning technique, meaning it doesn't build a model during the training phase but rather waits until a prediction is needed. This technique involves approximating a function locally, which is useful for tasks like classification and regression. In the case of classification, KNN assigns weights to neighboring data points based on their distance from the query point. For instance, if a neighbor is closer (with a distance of 'd' units), it gets a higher weight (1/d), signifying that its contribution to the prediction is more significant than that of distant neighbors. This prioritization of nearest neighbors helps KNN make predictions based on the majority class among its k-nearest neighbors.

One of the notable advantages of KNN is its minimal time complexity during training. Unlike many other algorithms that require extensive computational resources and complex model training procedures, KNN's training phase is straightforward and primarily involves computing the Euclidean distance between data points. This simplicity contributes to the algorithm's efficiency and ease of implementation, making it particularly suitable for smaller datasets or situations where quick predictions are required. However, it's essential to note that KNN's performance can be sensitive to the choice of the distance metric and the value of 'k' (the number of neighbors considered), requiring careful tuning for optimal results.

Figure 5.2: Working of kNN

5.2 Implementation of SVC

In the process of classifying tumors using a Support Vector Classifier (SVC) after an 8-layer Convolutional Neural Network (CNN) model, the CNN serves as the initial feature extractor from tumor images. This 8-layer CNN structure involves convolutional layers for identifying patterns in the images and pooling layers for reducing dimensionality. The output layer of the CNN employs softmax activation, providing probabilities for tumor classes. Subsequently, the SVC, configured with a C value of 1 for regularization and a linear kernel, refines the classification using these probabilities or extracted features1‘. The linear kernel is chosen due to the likelihood that the CNN's feature representations are already linearly separable or nearly so in the feature space. The C value in an SVC (Support Vector Classifier) is a regularization parameter that controls the trade-off between achieving a low training error and keeping the model simple. A smaller C value leads to a softer margin, allowing more margin violations (misclassifications) but potentially leading to a more generalized model. On the other hand, a larger C value results in a harder margin, aiming to minimize margin violations even if it means a more complex model that might overfit the training data. C = 1 signifies a moderate regularization strength. It strikes a balance between allowing some margin violations (which can be useful for handling noisy data or small overlapping classes) while still aiming to keep the model relatively simple and generalizable. This combined approach leverages deep learning's feature extraction capabilities with traditional machine learning's adaptability, leading to effective tumor classification.

5.3 Implementation of kNN

The k value in the k-NN algorithm defines how many neighbors will be checked to determine the classification of a specific query point. If k=1, the instance will be assigned to the same class as its single nearest neighbor. Defining k can be a balancing act as different values can lead to overfitting or underfitting. Lower values of k can have high variance, but low bias, and larger values of k may lead to high bias and lower variance. The choice of k will largely depend on the input data as data with more outliers or noise will likely perform better with higher values of k. Overall, it is recommended to have an odd number for k to avoid ties in classification, and cross-validation tactics can help you choose the optimal k for your dataset.

For the classification of brain tumors using the k-Nearest Neighbors (k-NN) algorithm, a k value of 20 has been chosen. This decision implies that when predicting the class of a specific brain tumor, the algorithm will consider the characteristics and features of the 20 nearest neighboring tumors in the feature space. This choice of k=20 reflects a strategy to reduce the influence of individual outlier data points, handle potential class imbalances effectively, and create a more robust classification model that is less sensitive to noise.

5.4 Confusion matrix and ROC of SVC and kNN Classifier

For evaluating the performance of model involves the use of various metrics, including the Receiver Operating Characteristic (ROC) curve and the confusion matrix. The ROC curve is a graphical representation used to evaluate the performance of a binary classifier. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings.The area under the ROC curve (AUC-ROC) provides a single measure of overall performance: the higher the AUC, the better the model is at distinguishing between the positive and negative classes. A confusion matrix is a table that is used to describe the performance of a classification model on a set of test data for which the true values are known. It allows us to see how well the model is performing in terms of correctly and incorrectly classified instances for each class.

Here we have shown the roc and the confusion matrix of SVC and KNN classifier for the classification of types of brain tumours mri images .

Figure 5.3: Confusion Matrix of SVC Training

Figure 5.4: Confusion Matrix of SVC Testing

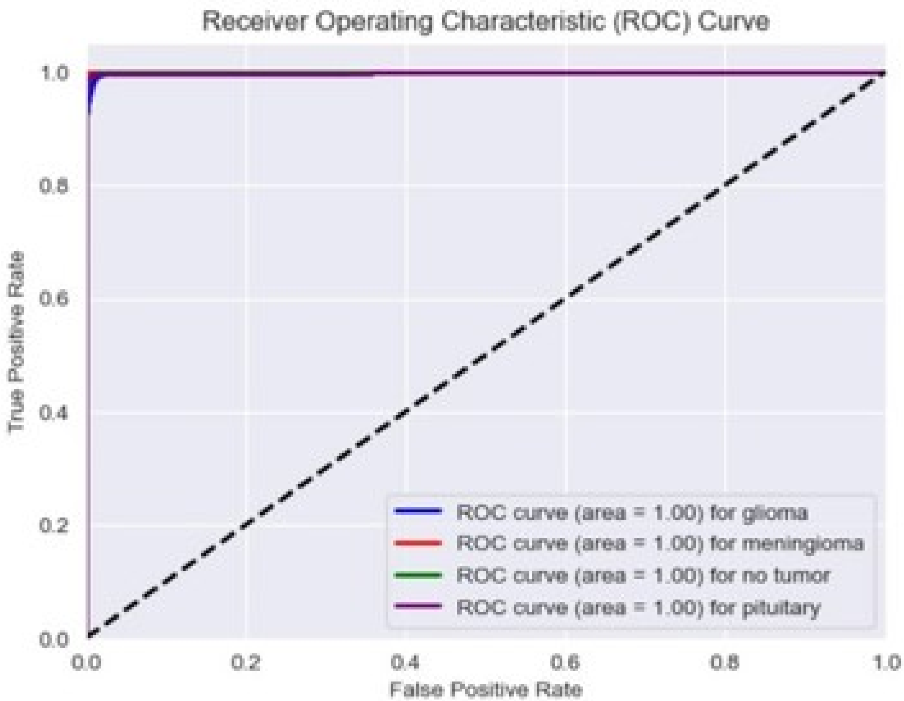

Figure 5.5: ROC of SVC Training

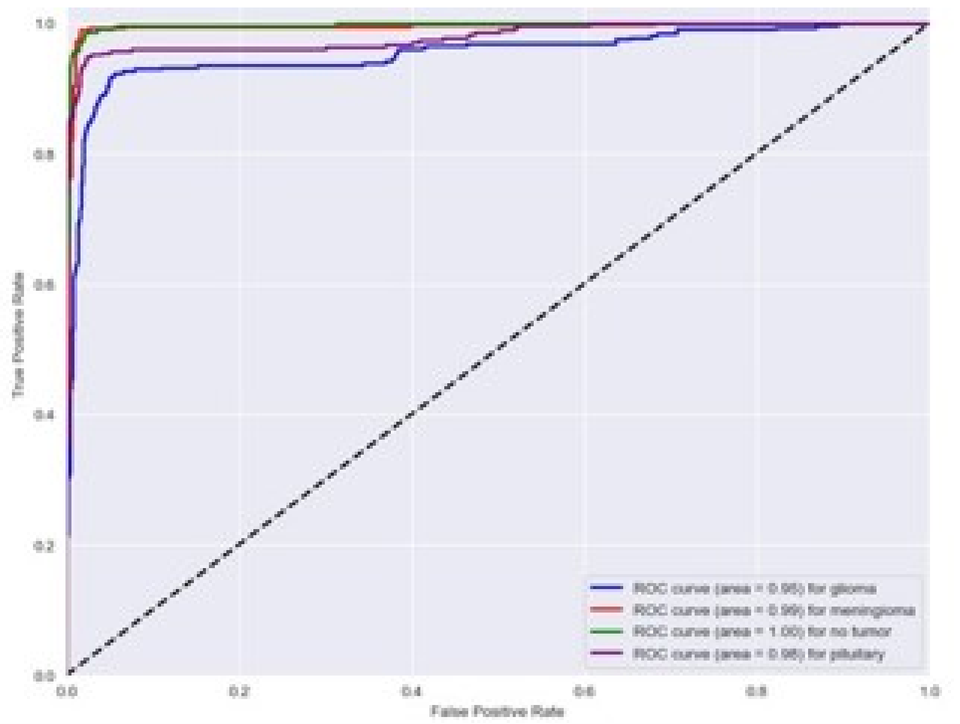

Figure 5.6: ROC of SVC Training

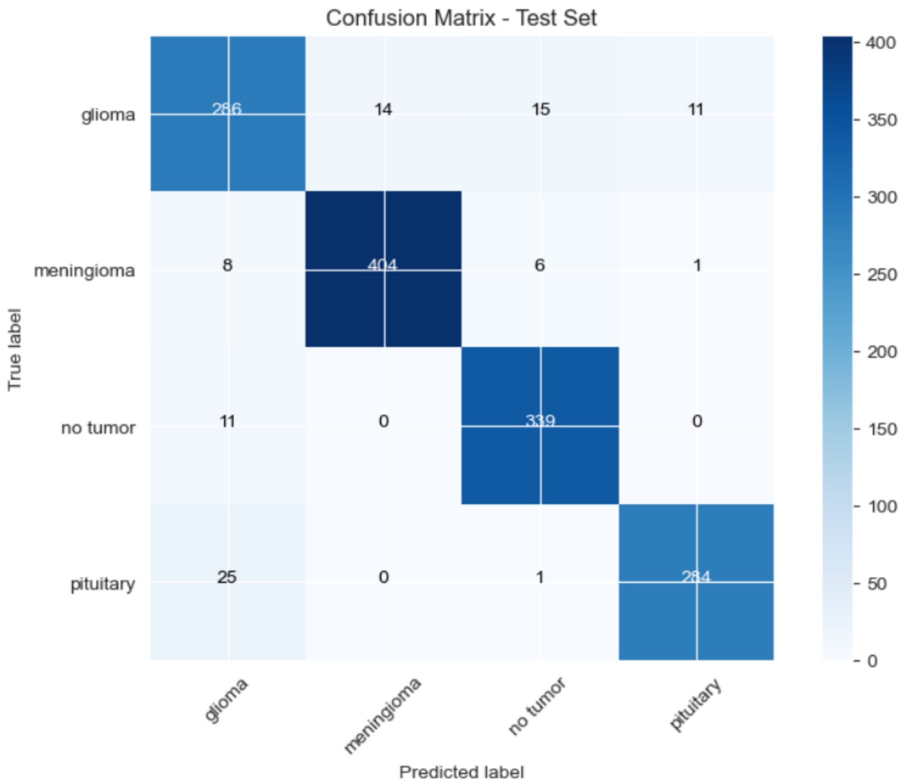

Figure 5.7: Confusion Matrix of kNN Training

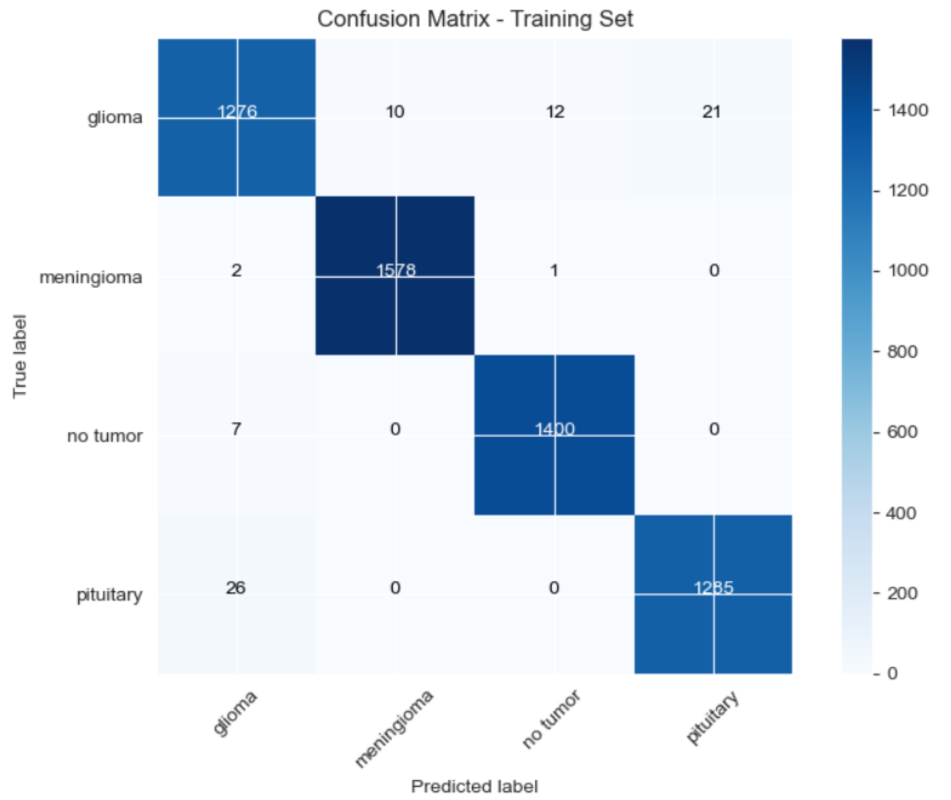

Figure 5.8: Confusion Matrix of kNN Testing

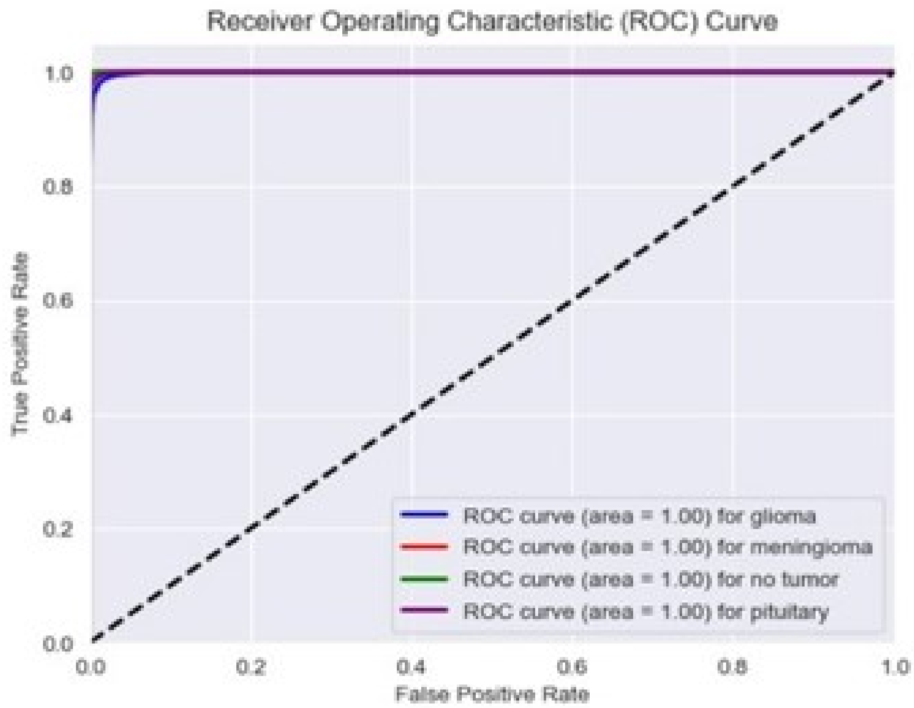

Figure 5.9: ROC of kNN Training

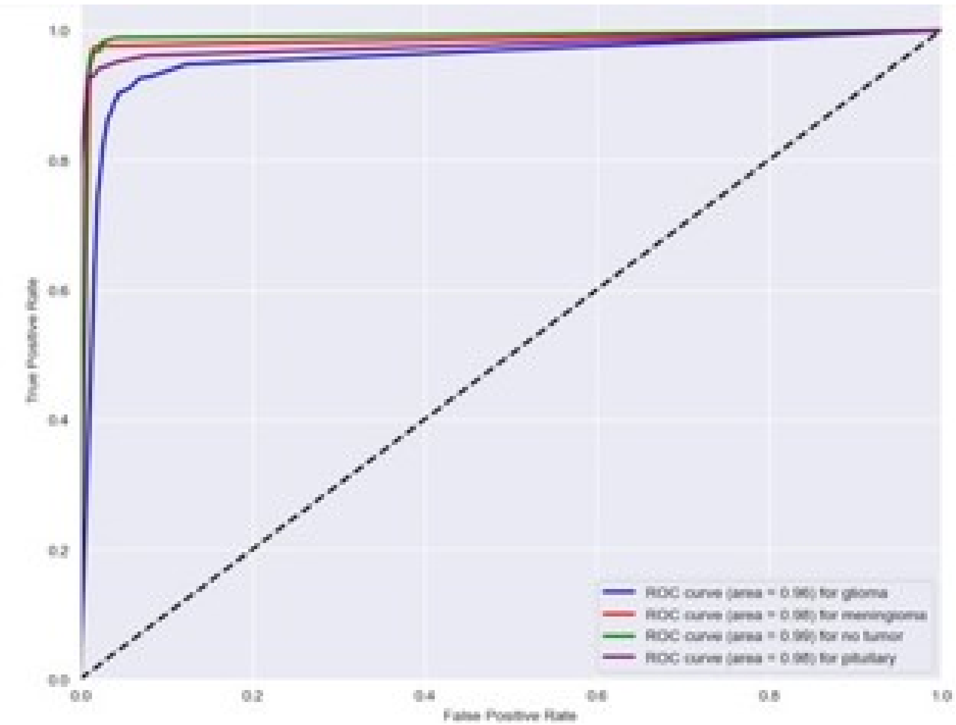

Figure 5.10: ROC of kNN Training

CHAPTER 6

Results and Conclusion

We evaluated the models based on accuracy, precision, recall, and F1-score values. Each metric provides a different perspective on the models' performance, offering a comprehensive assessment of their capabilities in brain tumor detection and classification. Accuracy measures the overall correctness, precision indicates the proportion of true positive results among all positive results, recall assesses the ability to identify all relevant instances, and F1-score harmonizes precision and recall into a single metric. Finally, we compare the three models—VGG16, SVC, and KNN—using these performance metrics to determine the most accurate and effective model for brain tumor classification. The results are presented in the following tables of performance metrics, highlighting the superior performance of the VGG16 model.

Table 6.1: Performance Matrix of VGG16 Model

Class	**Glioma**	**Meningioma**	**Pituitary**	**No-Tumor**
Accuracy	0.97	0.97	0.97	0.97
Precision	0.97	0.93	0.99	1.00
Recall	0.97	0.96	0.97	0.99
F1-Score	0.97	0.95	0.98	1.00

Table 6.2: Performance Matrix of SVC Model

Class	**Glioma**	**Meningioma**	**Pituitary**	**No-Tumor**
Accuracy	0.93	0.93	0.93	0.93
Precision	0.85	0.97	0.95	0.94
Recall	0.90	0.95	0.89	0.97
F1-Score	0.87	0.96	0.92	0.95

The results of this project shed light on the outstanding performance of the VGG16 Convolutional Neural Network (CNN) model compared to other classifiers like the Support Vector Classifier (SVC) and K-Nearest Neighbors (KNN) classifier in the domain of brain tumor detection and classification. With an accuracy rate of 97%, the VGG16 model stands out as a top performer, showcasing its ability to accurately identify and categorize brain tumors when presented with medical imaging data.

Table 6.3: Performance Matrix of kNN Model

Class	Glioma	Meningioma	Pituitary	No-Tumor
Accuracy	0.93	0.93	0.93	0.93
Precision	0.87	0.97	0.96	0.94
Recall	0.88	0.96	0.92	0.97
F1-Score	0.87	0.97	0.94	0.95

The exceptional accuracy achieved by this project's VGG16 model is attributed to its sophisticated architecture, tailored to extract intricate features and patterns from images, especially in medical imaging scenarios where precision is critical. Leveraging multiple layers including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification, the VGG16 model demonstrates its adeptness in navigating complex image data and making informed predictions.

The high accuracy demonstrated by this project's VGG16 model holds significant implications for medical practitioners and researchers alike. Accurate detection and classification of brain tumors are paramount in clinical settings for devising appropriate treatment plans and ensuring optimal patient outcomes. The robust performance of the VGG16 model in this project suggests its potential as a valuable tool in assisting medical professionals with accurate diagnosis and treatment recommendations.

Furthermore, this project underscores the importance of leveraging advanced deep learning techniques, such as CNNs, in medical image analysis. The ability of CNNs like the VGG16 model to automatically learn hierarchical representations of features from data makes them well-suited for tasks where intricate details and subtle patterns are crucial for accurate analysis.

In conclusion, the exceptional accuracy demonstrated by this project's VGG16 CNN architecture in brain tumor detection and classification positions it as a promising technology with the potential to enhance diagnostic accuracy and contribute to advancements in medical imaging analysis. Continued research and exploration of CNN-based approaches hold promise for further refining and optimizing brain tumor detection methodologies in the medical field.

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