An efficient ML approach to detect brain tumor using MRI images

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

Brain tumors have become the most leading causes of death worldwide. Brain tumors can be fatal, have a severe impact on quality of life, and completely alter a patient's and their loved ones' lives. Early diagnosis of brain tumors is really important as they spread quickly. But one of the most challenging tasks in medical image processing is tumor detection. Medical data has revealed that manual classification with human assistance can result in incorrect prediction and diagnosis. Magnetic resonance imaging (MRI) is the most effective method for finding brain tumors. Recently, deep learning algorithms have shown promising outcomes for enhancing the efficiency of brain tumor detection and identification from MRI. CNNs are highly common in deep learning, where they are used to solve many image processing, computer vision, and emerging area challenges. The technique CNN performs is to obtain an image, assign it a weight based on the various elements in the image, and then separate them from one another. In our paper our main target will be the detection of brain tumor and classify the tumor stages from the image segmentation using Image Processing, Deep Learning, CNN.

Keywords: Brain Tumor; CNN; Machine Learning; Deep Neural Network; Magnetic resonance imaging (MRI); KNN.

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First and foremost, glory be to Allah the Greatest, with whose help we were able to finish writing our thesis without too many setbacks. Secondly, we would like to thank our parents, who are always there for us in any situation. Thirdly, we would like to thank our supervisor, Dr. Md. Ashraful Alam, for his kind assistance and suggestions during our work. He came to our aid anytime we needed it.

Contents

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List of Acronyms

Several symbols and abbreviations that will be used later in the document's body are described in the following list.

- AI: Artificial Intelligence
- CNN: Convolutional Neural Network
- KNN: K-Nearest Neighbor
- ML: Machine Learning

Chapter 1

Introduction

1.1 Context of Brain Tumor

Brain Tumor is one of the most serious, widespread, and potentially deadly diseases around the world. A mass or growth of aberrant brain cells is known as a brain tumor. Brain tumors are dangerous because they can press on or spread into healthy regions of the brain. Brain tumors come in a wide variety of forms. It can be benign (noncancerous) or malignant (cancerous). Some tumors spread quickly, while others spread slowly. They may even be serious if they block the movement of fluid around the brain, since this may increase the pressure inside the skull. A person might occasionally be born with modifications to one or more of these genes. Further harm may subsequently result from environmental variables such earlier cancer treatment or exposure to high radiation levels from X-rays. In other circumstances, the genetic damage caused by the environment might be the only factor. The location, type, size, and functions that the damaged portion of the brain control all affect the symptoms of a brain tumor. Symptoms of brain tumors are not always noticeable. In fact, meningioma, the most frequent brain tumor in adults, frequently progresses undetected because of its slow growth. Until a tumor is large enough to interfere with healthy brain tissue, symptoms might not appear. Although they most frequently affect elderly persons, they can happen to anyone at any age. The most common cancer-related cause of death in children under the age of 14 is brain tumors. Also, it has been found that men are more likely than women to get brain tumors.
Magnetic resonance imaging (MRI) is generally the first step in the detection of a brain tumor (MRI) as MRI pictures themselves have great resolution and can clearly depict the structure, size, and location of brain tumors[1]. MRI can also reveal whether a cancerous tumor has metastasized (spread) to other regions of your body from its original site. Any cancers or abnormalities in the bone and soft tissue structures will be visible on those scans. A neoplasm, sometimes known as a tumor, is an abnormal growth or collection of cells. Deep Learning trains machines or computers to learn from experience, classify, and recognize data or images similarly to how a human brain does. Deep Learning has become a successful method for analyzing massive data. In numerous scientific studies, machine learning and deep learning algorithms are used to detect brain tumors. It takes relatively little time to identify a brain tumor when these algorithms are applied to MRI scans, and the improved accuracy simplifies patient care[2]. The radiologist can make speedy decisions thanks to these predictions. CNN (Convolutional Neural Networks), is

a type of artificial neural networks used in deep learning and are usually utilized for object and picture recognition and classifications. CNNs are essential to many activities and purposes, including computer vision challenges like segmentation and localization and image processing issues[3].
Deep learning and image segmentation have the potential to detect brain tumors since they provide a visual depiction of the tumor's stage. According to the tumor stages, it will be easy to start treatment as soon as possible, and hopefully it will be feasible to lower the number of deaths caused by brain tumors[4].
We want to make a beneficial influence on the field of medical imaging by applying our efficient ML approach for brain tumor detection and by providing a trustworthy and automated tool to support medical practitioners in accurate tumor diagnosis. If this strategy is correctly implemented, patient outcomes may be improved, early intervention would be possible, and the entire diagnostic process might be made simpler.

1.2 Problem Statement

In the brain or spinal cord, a tumor first appears as a primary tumor. In the United States, there will be 24,810 primary malignant tumors of the brain or spinal cord in 2023, with 14,280 men and 10,530 women affected. Less than 1% of people will get this form of tumor. Brain tumors make up 85% to 90% of the major central nervous system (CNS) cancers. In 2020, 308,102 persons are anticipated to receive a primary brain or spinal cord tumor diagnosis worldwide. Additionally, 5,230 children under the age of 20 are anticipated to receive a CNS tumor diagnosis in the US in 2023. A significant issue in the area of medical imaging is the diagnosis of brain cancers using MRI images. These images must be carefully evaluated by medical professionals, which takes time and might be inaccurate. In order to consistently and automatically identify brain tumors from MRI data and provide critical diagnostic support to medical professionals, an efficient machine learning (ML) as well as deep learning approach is necessary. Benign tumors are potentially hazardous. They have the potential to injure and compress portions of the brain, resulting in serious malfunction. A benign brain tumor that is in a critical part of the brain can be fatal. A benign tumor may very infrequently develop into a malignant one. There are many methods and algorithms to detect brain tumors. A CT scan or MRI can be used to examine the physiology of the brain tumor. MRI(magnetic resonance imaging) is a form of scan that creates high-quality images of the inside of the body and bodily parts like the brain, bones, joints, heart, blood vessels, and internal organs using powerful magnetic fields and radio waves.

1.3 Research Objectives

This research aims for the detection of brain tumors and classify the tumors from brain images. To elaborate, our experiment has been done to find adaptable and practical deep learning and machine learning algorithms so that we can find a working procedure that gives us an acceptable accuracy of brain tumor detection and classification. Here we have given our future expectations that can be done from our work:

1. Doctors can determine from classified images that in which region the tumor has grown from our work.

2. Our work will ensure accurate diagnosis and effectiveness. Early brain tumor detection is essential for treatment planning.

3. From our work, an early discovery of a brain tumor can improve the chances that the patient will recover after treatment.

4. Researchers can find greater accuracy from our work that makes it possible to treat patients more efficiently by using deep learning and machine learning to predict brain tumors from MRI images.

Chapter 2

Literature Review

Chattopadhyay, Maitra[5] proposed a methodology that consists of some customisations and some new operations along with the traditional way. They divided their work into 3 stages. To elaborate the first stage, they changed the fundamentals of the CNN model. They used a 9 layer CNN model consisting of 14 stages and hidden layers. Moreover, they created a convolutional kernel convoluted with input layer administering with 32 convolutional filters of size 2*2 with the support of 3 tensor channels. Also, they resized their input images into a constant size of 128*128*3. Furthermore, They used ReLU, a piecewise linear operation which will output the input directly if it is positive otherwise it will output 0. Moreover, batch normalization has been applied to make the neural network quicker. Lastly, a 2*2 Max pooling operation for the CNN has been used. Now for the second stage, they again used convolutional filters and this time they increased them to 64. Now, following the 64 convolutional filters, batch normalization as well as max pooling methods has been used again before doing the flattening. Now in the third stage, they used flattening and 2 dense layers. The first dense layer has 512 hidden layers and the second dense layer has the final 2 layers. In the final layer they used softmax as an activation function. After choosing the activation function they choose their extension of optimization algorithm or gradient descent to be RMSProp. A note to be taken is that they also tried SVM and Sigmoid but Softmax gave them better results. Taking about the results, they showed that Sigmoid gave them 97.63% accuracy, 58.33% testing accuracy and evaluation of the model was 68.72% whereas Softmax gave them 99.74% accuracy, 93.78% testing accuracy and evaluation of the model was 97.71% when RMSProp was used as an extension of optimization algorithm. For AdaMax as an extension of the optimization algorithm, Softmax gave them 98.10% accuracy, 75% testing accuracy and evaluation of the model was 82.40%. Here, they used 2473 training images and 273 testing images.

Sajjad, Muhammad et al.[6] proposed an interesting methodology for multigrade tumor classification. To elaborate, they introduced a novel deep learning framework that can classify brain tumors into four different grades. This system consists of three main steps. The first step is tumor segmentation. Here, they used a fully automated deep learning based technique called InputCascadeCNN that uses two way processing of images. The second step is data augmentation. Here, due to lack of satisfactory amounts of data they extended their data through 30 parameters and 8 augmentation techniques (transformational and noise invariance techniques). Thus, each sample of the dataset extended into 30 samples. The third step is delivering

the images into their CNN architecture. Here, they used VGG-19, a pretrained model, where they changed only the weights of fully connected layers for fine-tuning the model that classifies brain tumors into four different grades. They achieved an overall accuracy of 90.67%.

Brindha, Kavinraj et al.[7] detected brain tumor using deep learning implementing through two techniques. They are ANN and CNN. Here, the ANN model has seven layers. The first layer is the flatten layer and dense layer has been used as the next five layers. The last layer is the output layer, which is also a dense layer. Flatten layer converts the 256x256x3 images into a single dimensional array. The five dense layers are hidden layers where activation function is ReLU. The output layer represents the two classes(1 means it has a brain tumor, 0 means it does not have a brain tumor). Note to be taken is that the layers are constructed of neurons that are connected together. Here, the ANN model is trained by loading the training images and the validation images from the deataset. Now, once the model gets trained, it is tested using the test images' dataset. Now, they loaded same dataset into the CNN model. In the CNN model different types of processing got included like the ANN model. They are convolution, max pooling, flatten and dropout. Now for the layers, there are different layers like convolve layer that got applied on the input image with the ReLU an activation function. The fully connected layer is done by calling the dense method with ReLU as the activation function. The output layer represents two classes. Here the dataset is divided into training, validation and testing. Now, when the ANN model is used on a testing dataset, it gave 65.21% accuracy, whereas CNN gave 89%. Also, for the same class of dataset, precision is 65% for ANN and 89% for CNN. This dictates that CNN technique is much better compared to ANN technique. The researchers used a dataset from GitHub. The strength of this paper is that the researchers used both ANN and CNN techniques to build the models and showed which technique is better. The weakness of this paper is the self defined CNN model not being 100% accurate. There is some room for improvement. Here accuracy can be improved by giving more image dataset, applying image augmentation techniques and improving self defined CNN model.

Ankita[8] proposed a framework that basically has five modules. Dataset, Pre-processing, Part the information, Construct CNN show prepare Profound Neural arrange for ages, and classification. In the dataset, we will take numerous MRI pictures and take one as an input picture. In pre-processing the picture to encode the label and resize the picture. In part of the information, we set the picture as 80% Preparing Information and 20% Testing Information. At that point the picture is yes or no, in the event that the tumor is positive at that point it returns yes, and the tumor is negative then it returns no. Transfer learning may be an information-sharing strategy that decreases the measure of the preparation of information, the time and the computational costs when building profound learning models. Exchange learning makes a difference to exchange the learning of a pre-trained show to a modern show. Exchange learning has been utilized in different applications, such as tumor classification, computer program deformity expectation, movement acknowledgment and assumption classification.In this, the execution of the proposed Profound CNN demonstration has been compared with prevalent exchange learning approach. VGG16 may be a convolutional neural organism. The input of the 1 convolution layer is of settled measure 224x224 RGB picture. The picture is passed through a stack of convolutional layers, where the channels are utilized with a re-

ally little responsive field 3×3 (which is the littlest measure to capture the idea of left/right, up/down, center). Within the setups, it is additionally utilizing 1×1 convolution channels, and it can be seen as a straight change of the input channels. The convolution walk is settled to 1 pixel, and the spatial cushioning of convolution.All covered up layers are prepared with the amendment (ReLU) non-linearity. It is additionally famous that none of the systems (but for one) contain Neighborhood Reaction Normalization (LRN), such normalization does not progress the execution on the ILSVRC data-set, but leads to increased memory utilization and computation time. The strength of this paper is that the researchers used both VGG-16 and CNN techniques to build the models and showed which technique is better. The weakness of this paper is the CNN & VGG-16 model not being 100% accurate.

Gumaei, Hassan et al.[9] proposed a three-step method for effectively classifying brain tumors. First, a preprocessing phase converts intensity values from brain pictures. The most crucial characteristics are then retrieved using PCA-NGIST, a brand-new and effective hybrid technique. Finally, the RLEM classifier is used to categorize brain cancers.A new publicly available dataset of pictures of brain tumors is used to assess and compare the suggested approach's classification accuracy. This dataset includes 3064 brain scans from 233 people that show three different forms of brain tumors. Holdout (70% training, 30% testing) and 5-folds cross validation procedures are used in the trials.According to the experimental findings, the PCA-NGIST feature extraction approach is more accurate than PCA-GIST, GIST, and NGIST methods. Additionally, the results demonstrated that the proposed method outperformed the state-of-the-art in terms of classification rates. The proposed approach had an accuracy range of 91.51%–94.233%. We want to use the suggested method to resolve another biological classification issue and conduct a comparison analysis of several machine learning classifiers.

Sajid, Hussain, Sarwar [10] has presented a computer-aided diagnosis for glioma patients relies heavily on automated brain tumor segmentation. An automated hybrid model for brain tumor segmentation has been provided in this research in an effort to increase the effectiveness and efficiency of these methods. The hybrid model uses multimodal MRI data and deep convolutional neural networks to effectively segment MR images in the BRATS 2013 dataset.The hybrid model, which was created by fusing two- and three-path CNNs, has been shown to surpass cutting-edge methods in every significant performance metric. The proposed network segments the complete brain structure by classifying the central pixel of each patch using a patch-based technique. It predicts the output classes based on both local and global data and takes label relationships between pixels into consideration. The suggested model guarantees that learning is based on a correct distribution of labels and employs a two-phase training strategy to deal with unbalanced data. The over-fitting issue is addressed by the suggested technique, which integrates innovative developments in data preparation such as N4ITK bias field correction and uses dropout regularizer. The proposed network may be useful for a variety of segmentation tasks, according to a capability analysis of CNNs, and better performance may be obtained with more training examples.

Chapter 3

Different Types of Tumors

3.1 Meningioma

Meningiomas, which are typically benign tumors that arise from arachnoid cap cells, account for (13-26) percent of all cerebral tumors. Generally, they occur mostly in older people and women [11]. Here are some important facts concerning meningioma: Meningiomas form from the cells of the meninges, notably the arachnoid cells. These tumors are normally benign (non-cancerous), although they can be malignant (cancerous) in rare situations. The precise cause of meningiomas is uncertain. Certain risk factors, including as radiation exposure and a genetic disease known as neurofibromatosis type 2 (NF2), might, however, enhance the likelihood of developing these tumors. Multiple meningiomas are tumors that develop independently and in different locations. They are found in between 1 percent and 8 percent of patients diagnosed with meningioma. Multiple meningiomas are very common in NF2 patients, as well as in a few non-NF2 families with a familial meningioma propensity.[12] Symptoms of meningioma vary based on its size, location, and closeness to key brain regions. Headaches, seizures, limb weakness or numbness, changes in vision or hearing, difficulties with balance, and personality or cognitive changes are all common symptoms. Meningiomas are normally identified using a combination of a medical history evaluation, neurological examination, imaging tests (e.g., MRI or CT scan), and, in certain cases, a biopsy to confirm tumor type. Classification and Grading: Meningiomas are categorized into subtypes based on how they appear under a microscope. The World Health Organization (WHO) categorizes them on a scale of I to III, with grade I being the most common and typically less aggressive, and grades II and III being more aggressive and have a higher risk of infection. Treatment options for meningioma are determined by a number of criteria, including tumor size, location, grade, and the individual's overall health. Observation with regular monitoring, surgical removal, radiation therapy, and, in some circumstances, targeted medication therapy or chemotherapy are all treatment options. The prognosis for meningioma patients varies greatly. Grade I tumors have an excellent prognosis, with a low recurrence rate and a high survival rate. Tumors in grades II and III are more likely to recur and may necessitate more intensive therapy. The

long-term outlook is also affected by the tumor's location, as certain places are more difficult to treat than others.

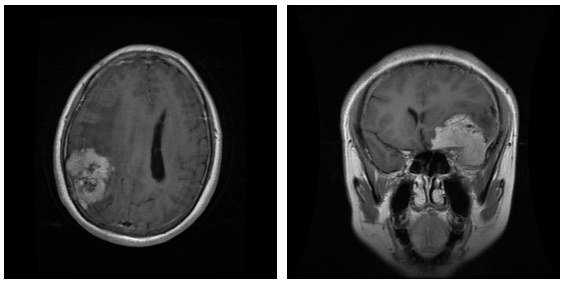

Figure 3.1: Samples of Meningioma

3.2 Glioma

Glial cells, which are the supporting cells of the central nervous system (brain and spinal cord), are the genesis of the tumor known as a glioma. The most frequent primary brain tumors are gliomas, which can either be benign (non-cancerous) or malignant (cancerous). The most frequent kinds of primary brain tumors are gliomas and meningiomas. Gliomas account for over 30 percent of all primary brain tumors and 80 percent of all malignant brain tumors, and they are responsible for the bulk of primary brain tumor mortality.[13] Here are some details about glioma tumors:

The type of glial cell from which a glioma develops determines its classification. Astrocytomas, oligodendrogliomas, ependymomas, and glioblastomas are among the common varieties. The most dangerous and typical kind of malignant glioma is glioblastoma. Although gliomas can affect people of all ages, they are often detected in adults. Particularly, glioblastomas are more common in elderly persons. Gliomas have uncertain specific causes. However, several risk factors, such as ionizing radiation exposure, specific genetic disorders (including neurofibromatosis and Li-Fraumeni syndrome), and a family history of gliomas, may raise the probability of acquiring these tumors.The location and size of the tumor affect the glioma's symptoms. Seizures, cognitive or memory issues, mood and behavioral disorders, muscular weakness or paralysis, speech difficulties, and visual or sensory impairments are among the common symptoms. Gliomas are normally identified by the study of the patient's medical history, a neurological examination, imaging tests (such as an MRI or CT scan to see the tumor), and frequently a biopsy to identify the kind and grade of the tumor. According to the World Health Organization (WHO) classification, gliomas are rated on a scale from I to IV. While grade III and IV gliomas (such as glioblastoma) are high-grade and more dangerous tumors, grade I and II gliomas are regarded as low-grade tumors. The kind, grade, location, and general health of the patient all affect the treatment options for gliomas. Surgery to remove as much of the tumor as feasible, radiation therapy, chemotherapy, tar-

geted therapy, and, in some circumstances, immunotherapy are all viable forms of treatment.
Patients get depressed soon after glioma surgery, and this depression usually increases over the next six months. It indicates that clinically significant depression is a typical consequence in high-grade glioma patients.[14] Treatment modalities can be applied singly or in combination. Depending on the kind, grade, location, and the patient's reaction to therapy, the prognosis for gliomas varies considerably. Due to their aggressive nature and propensity to recur, high-grade gliomas, especially glioblastoma, often have a worse prognosis. Individual instances can vary greatly, though, and some people may benefit from therapy and live longer.

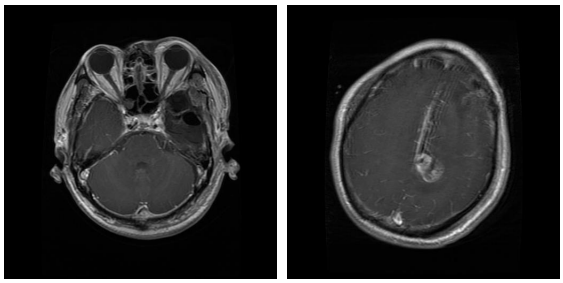

Figure 3.2: Samples of Glioma

3.3 Pituitary

A pituitary tumor, also known as a pituitary adenoma, is a tumor that develops in the pituitary gland, which is a tiny gland at the base of the brain. The pituitary gland is responsible for regulating hormone production and governing many body functions.[15] Here are some facts concerning pituitary tumors:

Pituitary tumors are categorized depending on the sort of cells that give rise to them and the hormones they produce. They can be functioning, which means they generate hormones, or non-functional, which means they do not. Prolactinomas (tumors that produce prolactin), growth hormone-secreting tumors (acromegaly), adrenocorticotropic hormone-secreting tumors (Cushing's disease), and non-functional tumors are common forms.

Pituitary tumors are rather common, with an estimated 10 percent to 20 percent of people having a minor pituitary tumor. Many of these tumors are non-cancerous (benign) and do not pose any serious health risks. Causes: The precise source of pituitary tumors is frequently unknown. Genetic mutations, some inherited disorders (e.g., multiple endocrine neoplasia type 1), and rare genetic syndromes (e.g., Carney complex) may all play a role in their development. Symptoms: Pituitary tumor symptoms vary based on the tumor kind, size, and hormone production. Headaches, vision issues (such as loss of peripheral vision), hormone imbalances (e.g., monthly irregularities, sexual dysfunction, growth abnormalities), exhaustion, weight fluctuations, and mood disorders are also prevalent symptoms.

Pituitary tumors are often identified using a combination of a medical history evaluation, physical examination, hormone level testing, and imaging procedures (e.g., MRI or CT scan) to visualize and analyze the tumor's features. Treatment Options:

Pituitary tumor treatment is dependent on a number of criteria, including tumor size, hormone production, and symptoms. Medication to reduce hormone production, surgery to remove the tumor (transsphenoidal surgery is the most common procedure), radiation therapy (conventional or stereotactic radiosurgery), or a combination of these approaches may be used as treatment options. Pituitary tumor prognosis varies based on the tumor type, size, and response to treatment. Many pituitary tumors, particularly tiny benign ones, can be adequately handled, and patients can live normal lives. Larger or more aggressive tumors, on the other hand needs continuation of treatment and monitoring.

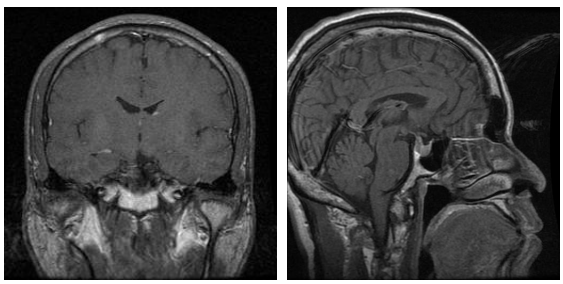

Figure 3.3: Samples of Pituitary

Chapter 4

Research Methodology

4.1 Proposed Workflow

Here, the proposed work plan consists of eight parts. The first part is data acquisition. The second part is data pre-processing. Moreover, the third part is data splitting. The fourth part is training the four convolutional neural network models. The fifth part is testing the four convolutional neural network models and acquire the accuracy of prediction of each model. Furthermore, the sixth part is loading the extracted feature and labels from the training and validation datasets into the KNN algorithm for training. The seventh part is loading the extracted feature from the testing dataset for prediction and acquiring the accuracy. Lastly, the eighth part is taking the average of probability of each class from every model and acquire the accuracy.

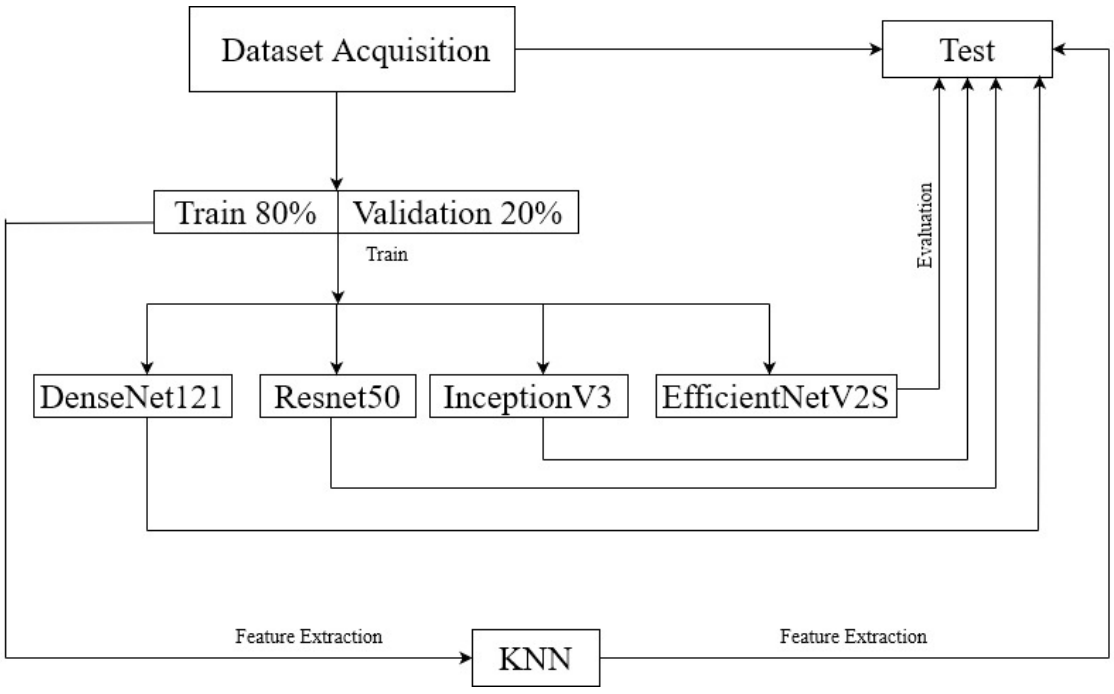

Figure 4.1: Work Procedure

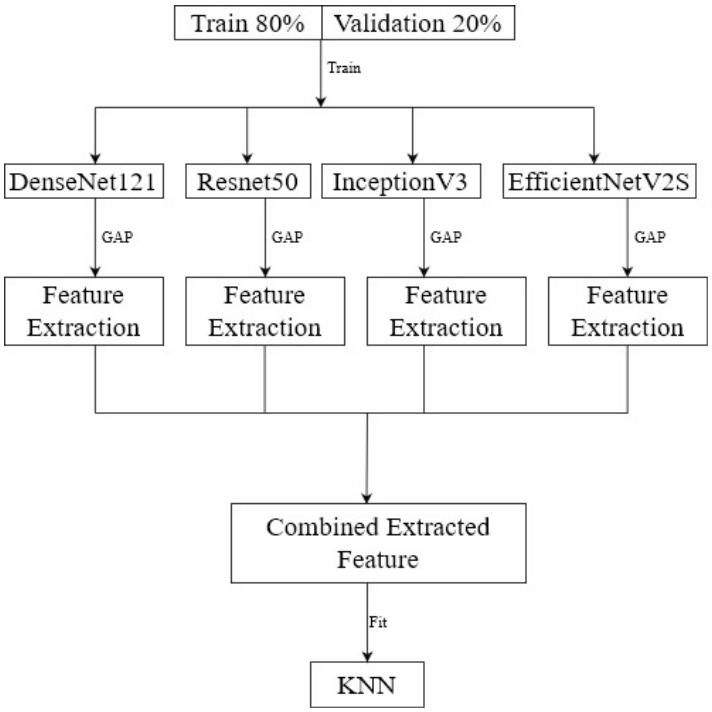

Figure 4.2: Work Procedure of Feature Extraction From Training & Validation Dataset

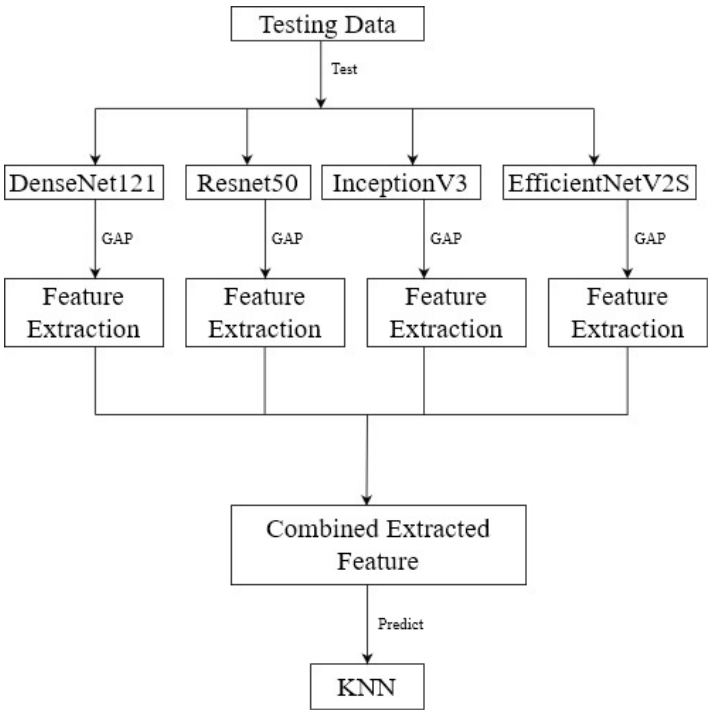

Figure 4.3: Work Procedure of Feature Extraction From Testing Dataset

4.2 Dataset

4.2.1 Dataset Details

This dataset contains 7022 images of human brain MRI images which are classified into 4 classes: glioma, meningioma, no tumor, pituitary. Here, the dataset is divided into two parts. One part is training which contains 5712 images. Here, class Glioma has 1321 images, class Meningioma has 1339 images, class Notumor has 1595 images and class Pituitary has 1457 images. Now, another part is testing which contains 1311 images. Here, class Glioma has 300 images, class Meningioma has 306 images, class Notumor has 405 images and class Pituitary has 300 images. We have shown a figure [4.1] showing some samples of our dataset along with four classes of training and testing datasets and their count in figure[4.2].

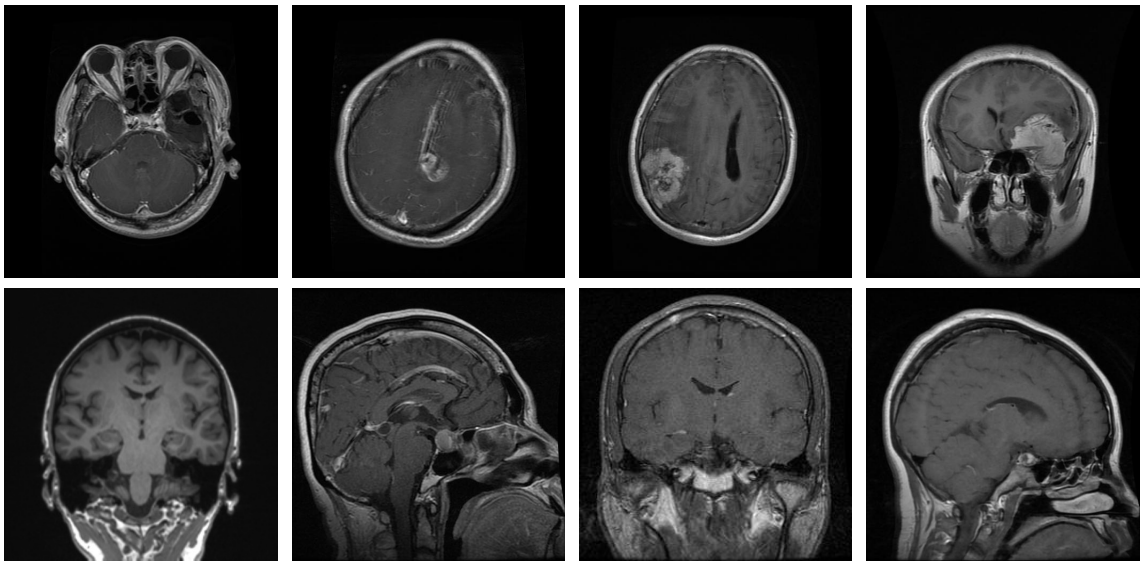

Figure 4.4: Samples of Dataset

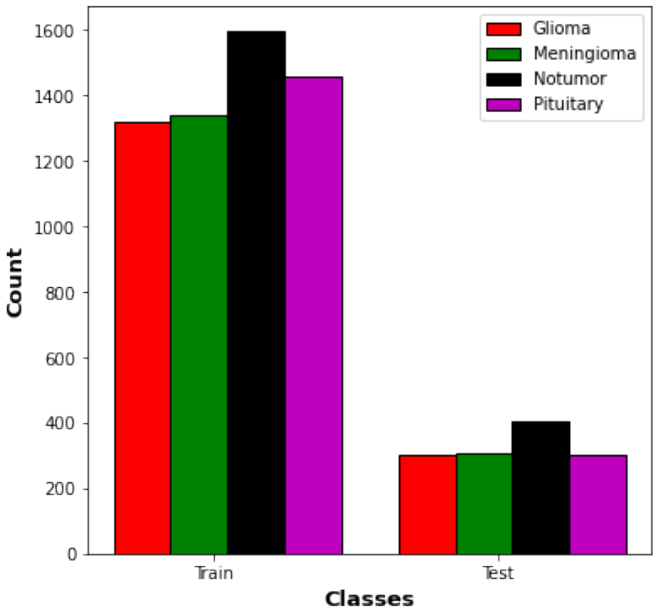

Figure 4.5: Classes VS Count

4.2.2 Dataset Preprocessing

In this part, we have set the shape of the all the images to 224×224×3. Moreover, we have normalized the images to have values between 0 and 1 by dividing with 255. Furthermore, we have done the splitting. Here, the dataset was already in two parts. One is training data and another one is testing data. Now, we have split the training dataset into two parts. One is the training dataset, which is 80 percent of the main training dataset. Another in the validation dataset, which is 20 percent of the main training dataset.

4.2.3 Dataset Augmentation

Here, we have used augmentation to reduce overfitting. We have used some augmentation techniques for the dataset. To elaborate, we have used rotation randomly from 0 to 40 degree. Moreover, we have used width shift as well as height shift randomly from 0 to 20 %. Furthermore, we have used image horizontal flipping randomly, shearing randomly from 0 to 20 % and lastly zooming of the images from randomly 0 to 20 %. Here we have given a figure[4.6] showing some augmented images from the dataset.

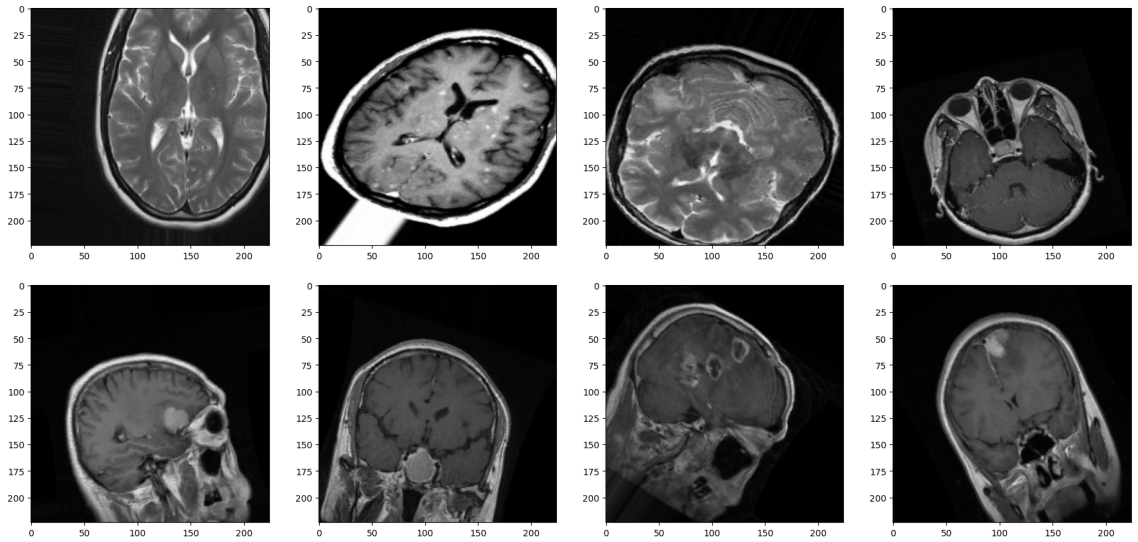

Figure 4.6: Sample of Augmented Images

4.3 Convolutional Neural Network Architectures

4.3.1 ResNet50

ResNet50 is a popular deep convolutional neural network architecture introduced by Microsoft Research in 2015. It belongs to the ResNet50 family and is widely used in computer vision tasks like image classification, object detection, and image segmentation.[16] ResNet50 stands out for its use of skip connections or residual connections, which enable information to flow directly from earlier to later layers, addressing the vanishing gradient problem. With 50 layers and a modular structure, ResNet50 consists of multiple stages and residual blocks. Each residual block contains convolutional layers with batch normalization and ReLU activation. The skip connections in ResNet50 are implemented as identity shortcuts, allowing the network to learn residual mappings. This architecture can capture both low-level and high-level features due to its deep and interconnected structure.[17] ResNet50 has been pretrained on large-scale datasets like ImageNet, providing it with generic features that can be fine-tuned for specific tasks. Overall, ResNet50 is a powerful and widely used architecture in deep learning for computer vision applications. Here, we have shown a figure[4.3] below of ResNet50 architecture.

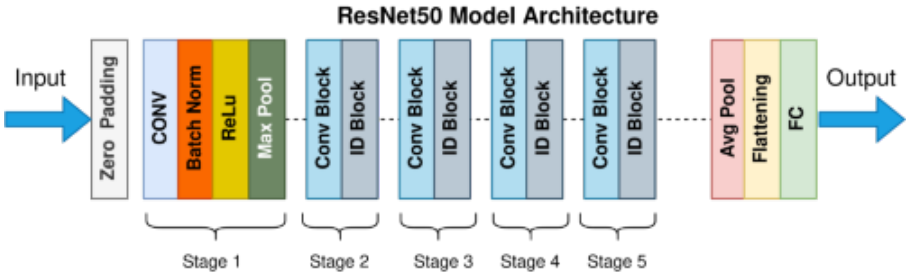

Figure 4.7: ResNet50 Model

4.3.2 EfficientNetV2S

EfficientNetV2S is an advanced deep neural network architecture that improves efficiency and performance for computer vision tasks. It uses compound scaling to optimize depth, width, and resolution, resulting in a well-balanced model. The "S" variant has fewer parameters and is lighter, making it suitable for resource-constrained scenarios. It utilizes efficient bottleneck blocks with depthwise separable convolutions and a squeeze-and-excitation module to reduce parameters while maintaining expressive power. The "Repetition Padding" training scheme addresses border artifacts, improving accuracy. EfficientNetV2S achieves state-of-the-art performance on benchmarks like ImageNet, making it ideal for real-time inference or environments with limited resources.[18] Here, we have shown a figure[4.4] below of EfficientNet architecture.

4.3.3 DenseNet121

DenseNet121 is a deep neural network architecture known for its dense connectivity and efficient parameter usage in image classification tasks. It addresses the vanishing gradient problem by densely connecting each layer to every other layer, allowing efficient information flow and feature reuse. The network consists of dense blocks where each layer's output is concatenated with preceding layers, enabling access to a wide range of feature representations. Transition layers compress information between dense blocks to maintain computational efficiency. DenseNet121 achieves excellent performance with fewer parameters due to its parameter efficiency.[19] It has achieved state-of-the-art results on benchmarks like ImageNet, outperforming previous architectures. DenseNet121 captures intricate image details and improves gradient flow during training. It is a powerful and robust model in image classification, demonstrating remarkable accuracy. Here, we have shown a figure[4.5] below of DenseNet121 architecture.

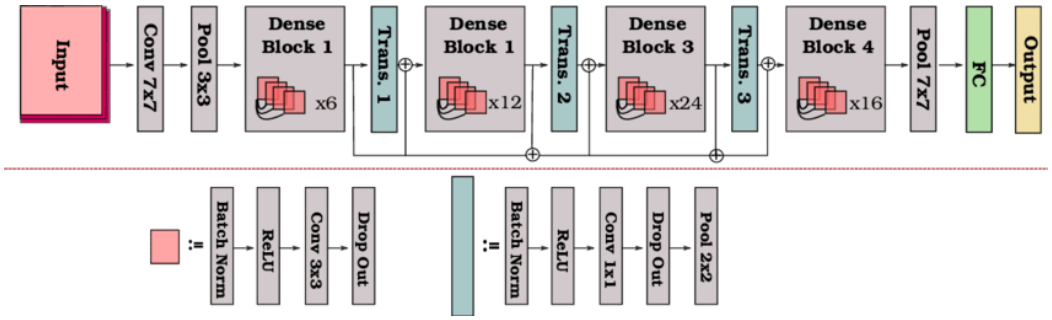

Figure 4.8: DenseNet121 Model

4.3.4 InceptiontV3

InceptionV3 is a convolutional neural network architecture known for its effectiveness in image classification and object detection tasks. It optimizes the balance between computational efficiency and representational power by using different-sized convolutional filters in its inception modules. These modules capture features at multiple scales and aggregate them efficiently. InceptionV3 has a deep architecture with stacked inception modules, allowing it to learn hierarchical representations. It incorporates dimensionality reduction techniques, like 1x1 convolutions, to reduce computational complexity.[20] The model also includes auxiliary classifiers for gradient flow and regularization during training. InceptionV3 achieves high accuracy with reasonable computational efficiency and has excelled in object detection. It is widely used as a backbone architecture in state-of-the-art models. Here, we have shown a figure[4.6] below of InceptionV3 architecture.

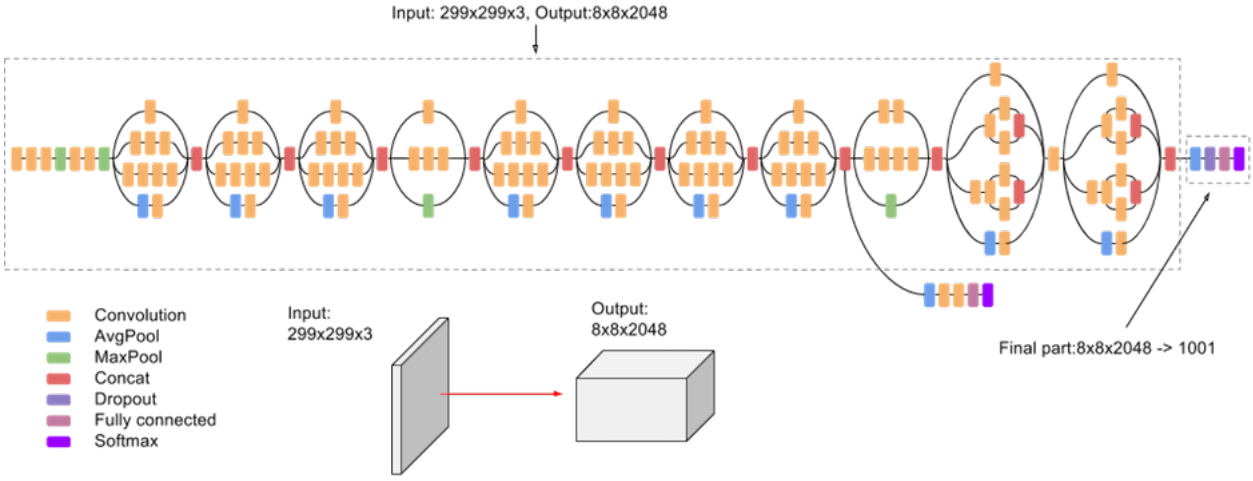

Figure 4.9: InceptionV3 Model

4.4 KNN A Machine Learning Algorithm

The K-nearest neighbors (KNN) technique is a form of supervised machine learning (ML) algorithm that can be used for both classification and regression predicting tasks. [21] The KNN technique, which is well-known for its simplicity and low error rate, is often employed in pattern recognition and data mining for labeling. It is an instance-based learning method in which the algorithm learns directly from the training data rather than constructing a model. [22] The K-Nearest Neighbors algorithm is a non-parametric classification and regression approach. The input is made up of the k closest samples in each space. The K-Nearest Neighbors algorithm is an example of lazy learning. It predicts the classification of a new sample point using data from many classes. The neighbors are chosen from a set of items or items with similar properties or values which refers to a training dataset. KNN method uses the Euclidean distance, which is defined as a straight line between two places. Before applying the KNN method to a dataset its parameters must be scaled down to a normalized scale. The value of k is critical in the KNN algorithm for defining the number of neighbors. The input data should be used to determine the value of k in the k-nearest neighbors (k-NN) algorithm. A greater value of k would be preferable if the input data contained more outliers or noise. A lower K value can result in more lenient and potentially noisier rulings. KNN can handle both numerical and categorical data, making it useful for a variety of problems. As KNN predictions are based on actual instances from the training data, they are simple to interpret. The algorithm must compute the distance between the request instance and all of its training instances, which can take some time. The performance of KNN is affected by the value of K. Choosing an incorrect K value can result in faulty prediction. KNN involves storing the complete training dataset in memory when working with really big datasets. It must compare new instances to all previous ones.

Chapter 5

Result And Analysis

Here, we have trained 4 convolutional neural network models. Furthermore, we have tested them and acquired the accuracy, precision, recall, f1 score and confusion matrix of each model. After that, we have predicted the mean of the probability of each class of every model and calculated an accuracy.

Lastly, we have used KNN algorithm for prediction through extracted features to search for better accuracy, precision, recall, f1 score and confusion matrix.

5.1 Testing With ResNet50

We have started our testing with ResNet50. Here, we have imported weights from a convolutional neural network model trained on Imagenet dataset.

Also, we have set the batch size to 32 and learning rate to 1e-5. Moreover, we have run 50 epochs for the convolutional neural network model. We have used keras checkpoint for recording the best validation accuracy during the training period through every epoch. Here, the best validation accuracy the model gave us is 0.9668 on epoch 49. Now, we have saved the model that gave us best validation accuracy for testing purpose.

Finally, we move to the testing period. We have encoded the labels. Here, 0 represents glioma, 1 represents meningioma, 2 represents notumor and 3 represents pituitary. Now, after the testing the model on the testing dataset, the model gave us an accuracy of 97.55%. We have incorporated a figure[5.1] below showing a confusion matrix showing true positives and false positives. Also, a figure[5.2] showing training and validation accuracy and a figure[5.3] of training and validation loss curve. Lastly, we have given a table[5.1] showing the precision, recall and f1-score for every class.

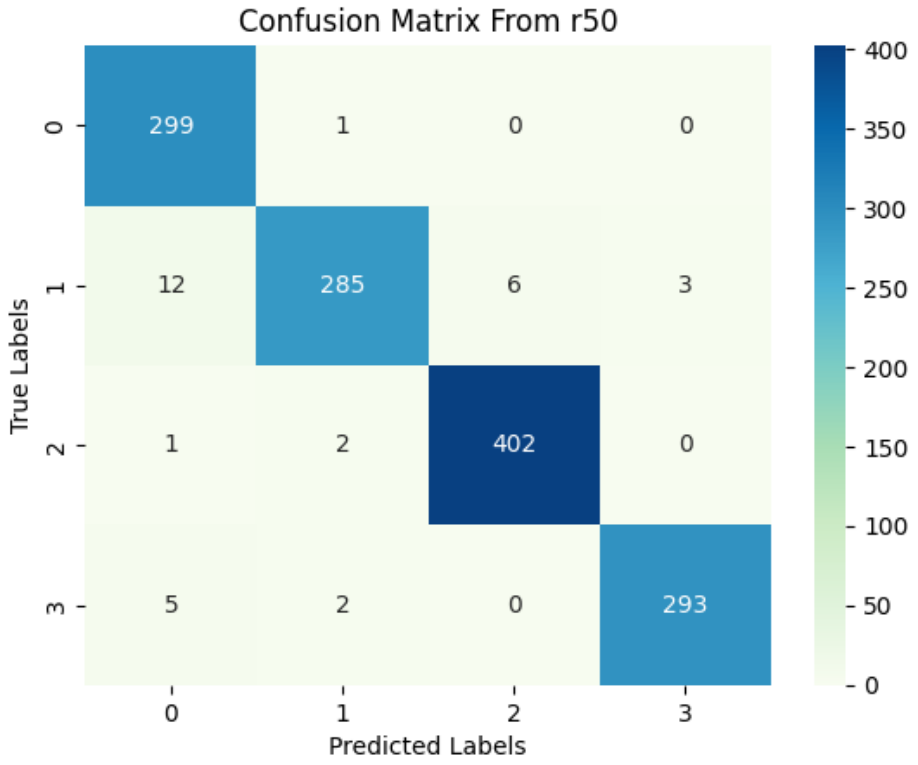

Figure 5.1: Confusion matrix Resnet50

Figure 5.2: Training Validation accuracy curves Resnet50

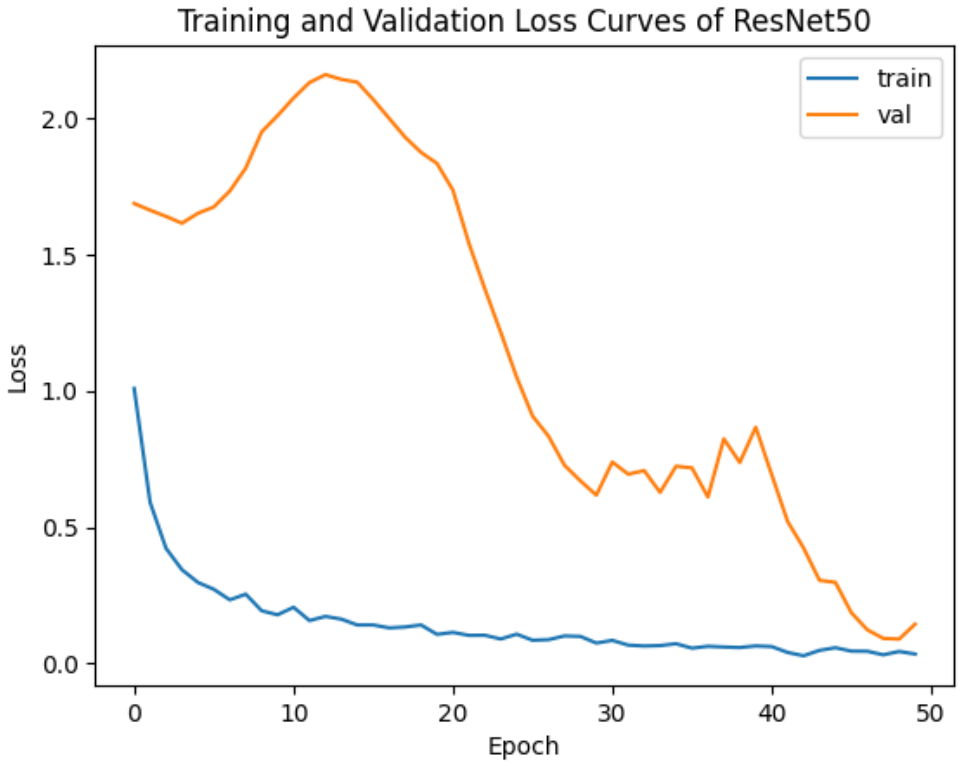

Figure 5.3: Training Validation loss curves Resnet50

Class	precision	Recall	f1-score
Glioma	0.94	1.00	0.97
Meningioma	0.98	0.93	0.96
Notumor	0.99	0.99	0.99
Pituitary	0.99	0.98	0.98

Table 5.1: The Precision, Recall and F1-score of ResNet50

5.2 Testing With EfficientNetV2S

After ResNet50, we have tested with EfficientNetV2S. Here, we have imported weights from a convolutional neural network model trained on Imagenet dataset. Also, we have set the batch size to 32 and learning rate to 1e-5.
Moreover, we have run 50 epochs for the convolutional neural network model. We have used keras checkpoint for recording the best validation accuracy during the training period through every epoch. Here, the best validation accuracy the model gave us is 0.9633 on epoch 48. Now, we have saved the model that gave us best validation accuracy for testing purpose.

Finally, we move to the testing period. We have encoded the labels. Here, 0 represents glioma, 1 represents meningioma, 2 represents notumor and 3 represents pituitary. Now, after the testing the model on the testing dataset, the model gave us an accuracy of 97.10%. We have incorporated a figure[5.4] below showing a confusion matrix showing true positives and false positives. Also, a figure[5.5] showing training and validation accuracy and a figure[5.6] of training and validation loss curve. Lastly, we have given a table[5.2] showing the precision, recall and f1-score for every class.

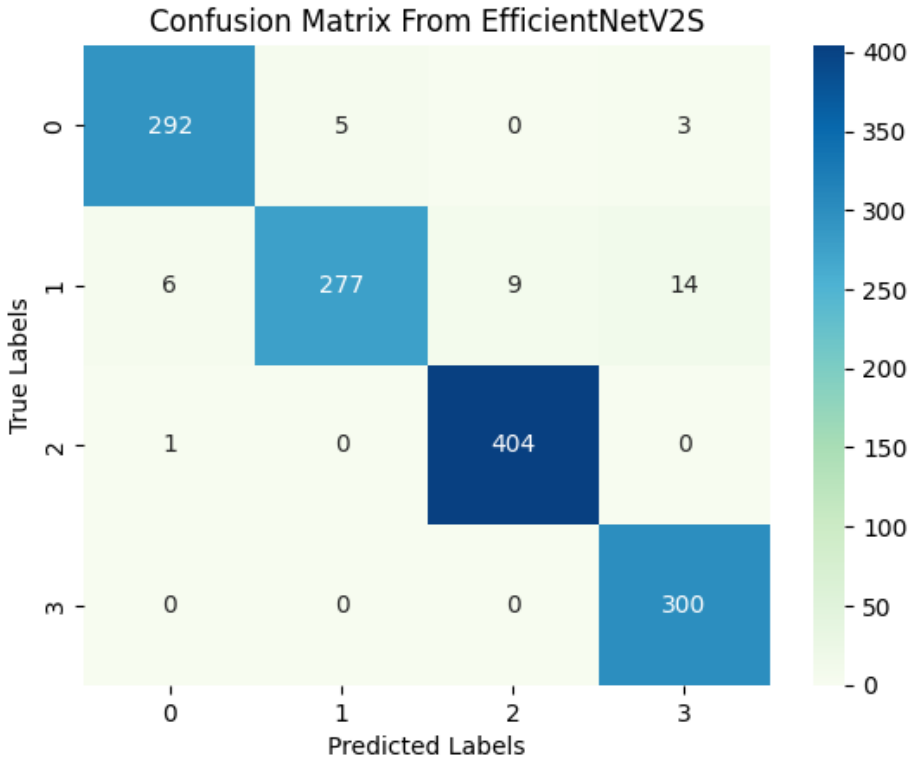

Figure 5.4: Confusion matrix EfficientV2S

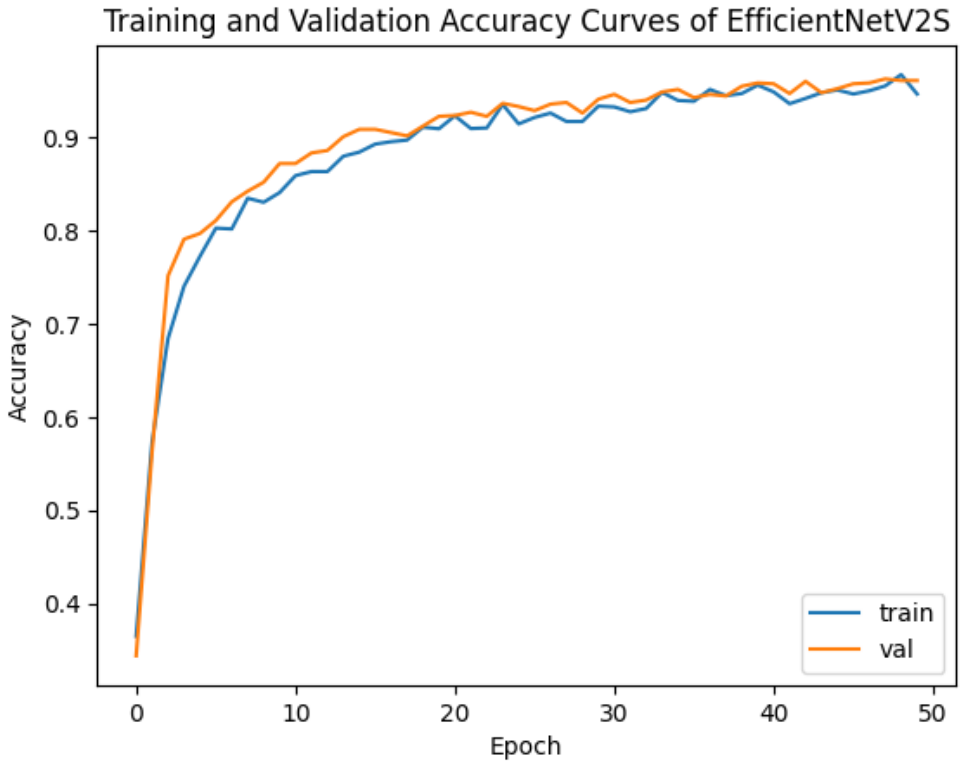

Figure 5.5: Training Validation accuracy curves EfficientV2S

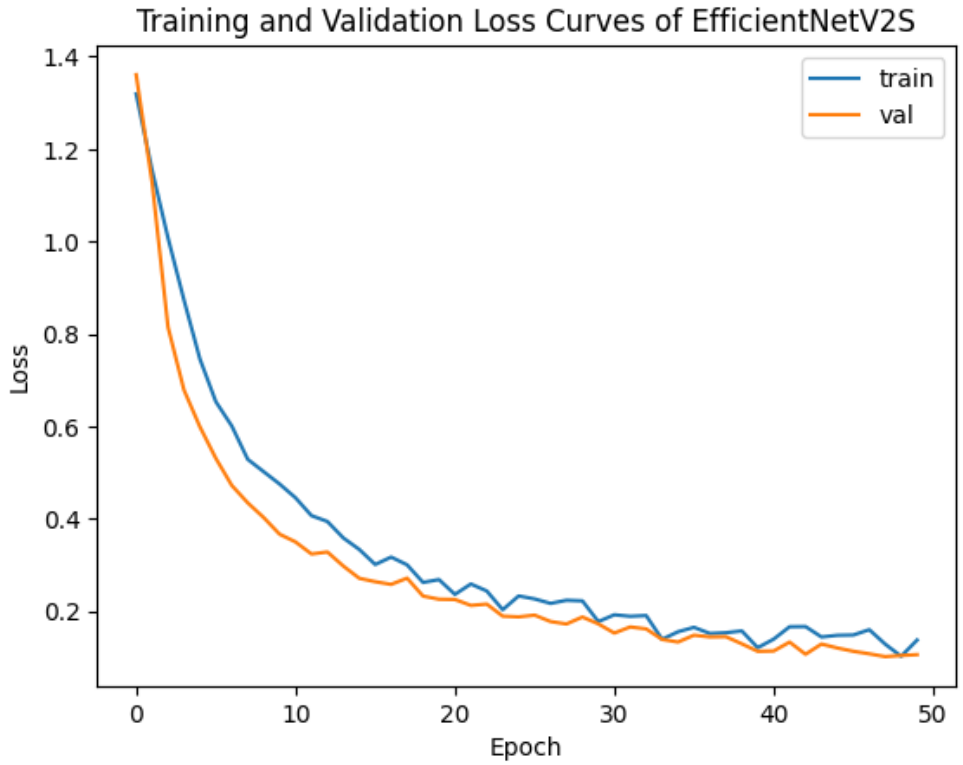

Figure 5.6: Training Validation loss curves EfficientV2S

Class	precision	Recall	f1-score
Glioma	0.98	0.97	0.97
Meningioma	0.98	0.91	0.94
Notumor	0.98	1.00	0.99
Pituitary	0.95	1.00	0.97

Table 5.2: The Precision, Recall and F1-score of EfficientNetV2S

5.3 Testing With InceptionV3

After EfficientNetV2S, we have tested with InceptionV3. Here, we have imported weights from a model trained on Imagenet dataset. Also, we have set the batch size to 32 and learning rate to 1e-5. Moreover, we have run 50 epochs for the model. We have used keras checkpoint for recording the best validation accuracy during the training period through every epoch. Here, the best validation accuracy the model gave us is 0.9650 on epoch 45. Now, we have saved the model that gave us best validation accuracy for testing purpose. Finally, we move to the testing period. We have encoded the labels. Here, 0 represents glioma, 1 represents meningioma, 2 represents notumor and 3 represents pituitary. Now, after the testing the model on the testing dataset, the model gave us an accuracy of 96.41%. We have incorporated a figure[5.7] below showing a confusion matrix showing true positives and false positives. Also, a figure[5.8] showing training and validation accuracy and a figure[5.9] of training and validation loss curve. Lastly, we have given a table[5.3] showing the precision, recall and f1-score for every class.

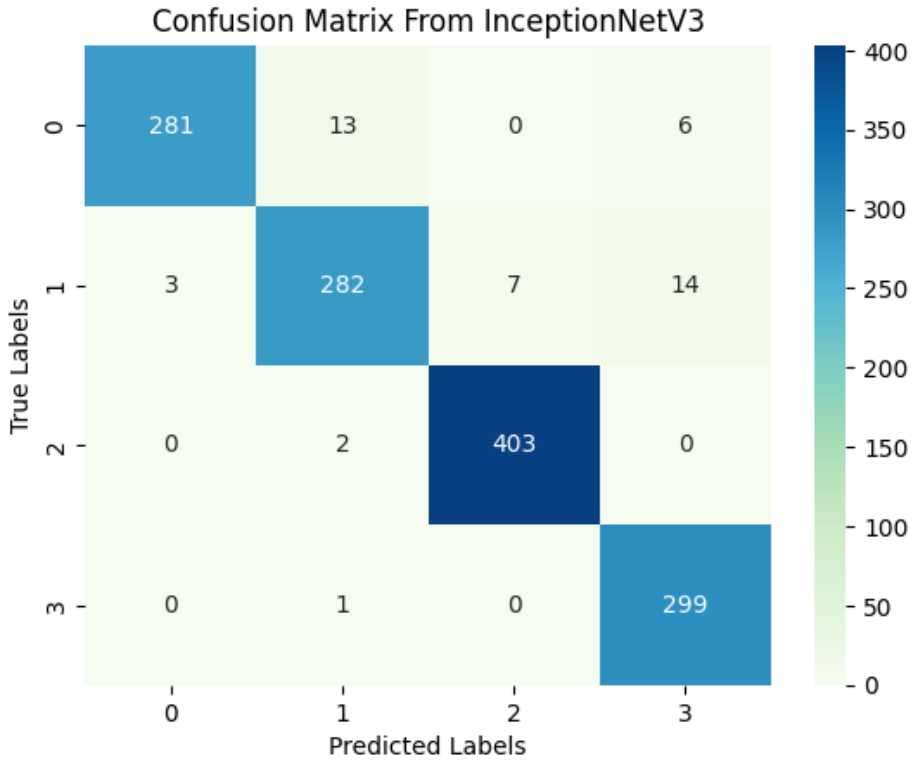

Figure 5.7: Confusion matrix InceptionV3

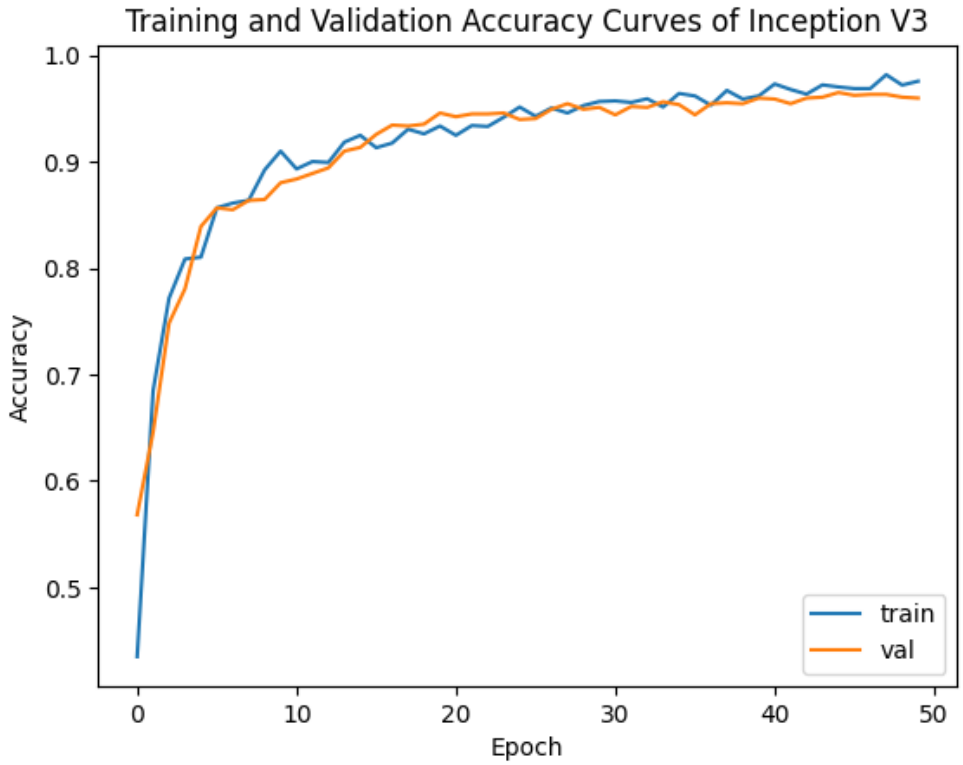

Figure 5.8: Training Validation accuracy curves InceptionV3

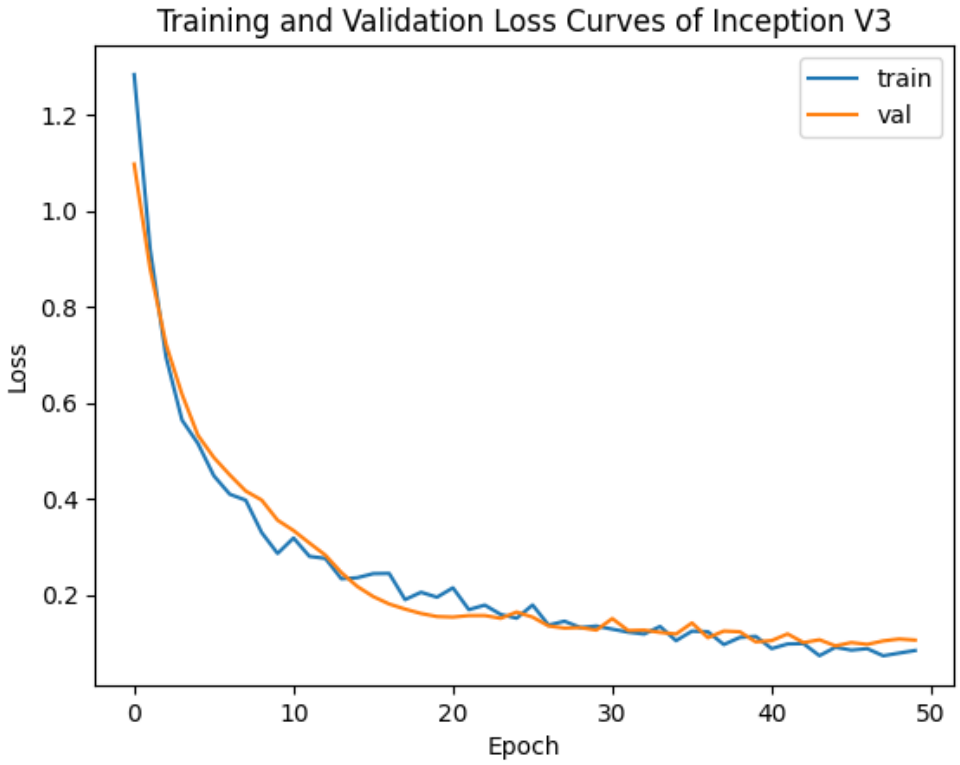

Figure 5.9: Training Validation loss curves InceptionV3

Class	precision	Recall	f1-score
Glioma	0.99	0.93	0.96
Meningioma	0.95	0.92	0.93
Notumor	0.98	1.00	0.99
Pituitary	0.93	1.00	0.96

Table 5.3: The Precision, Recall and F1-score of InceptionV3

5.4 Testing With DenseNet121

After InceptionV3, we have tested with DenseNet121. Here, we have imported weights from a model trained on Imagenet dataset. Also, we have set the batch size to 32 and learning rate to 1e-5. Moreover, we have run 50 epochs for the model. We have used keras checkpoint for recording the best validation accuracy during the training period through every epoch. Here, the best validation accuracy the model gave us is 0.9624 on epoch 47. Now, we have saved the model that gave us best validation accuracy for testing purpose. Finally, we move to the testing period. We have encoded the labels. Here, 0 represents glioma, 1 represents meningioma, 2 represents notumor and 3 represents pituitary. Now, after the testing the model on the testing dataset, the model gave us an accuracy of 97.33%. We have incorporated a figure[5.10] below showing a confusion matrix showing true positives and false positives. Also, a figure[5.11] showing training and validation accuracy and a figure[5.12] of training and validation loss curve. Lastly, we have given a table[5.4] showing the precision, recall and f1-score for every class.

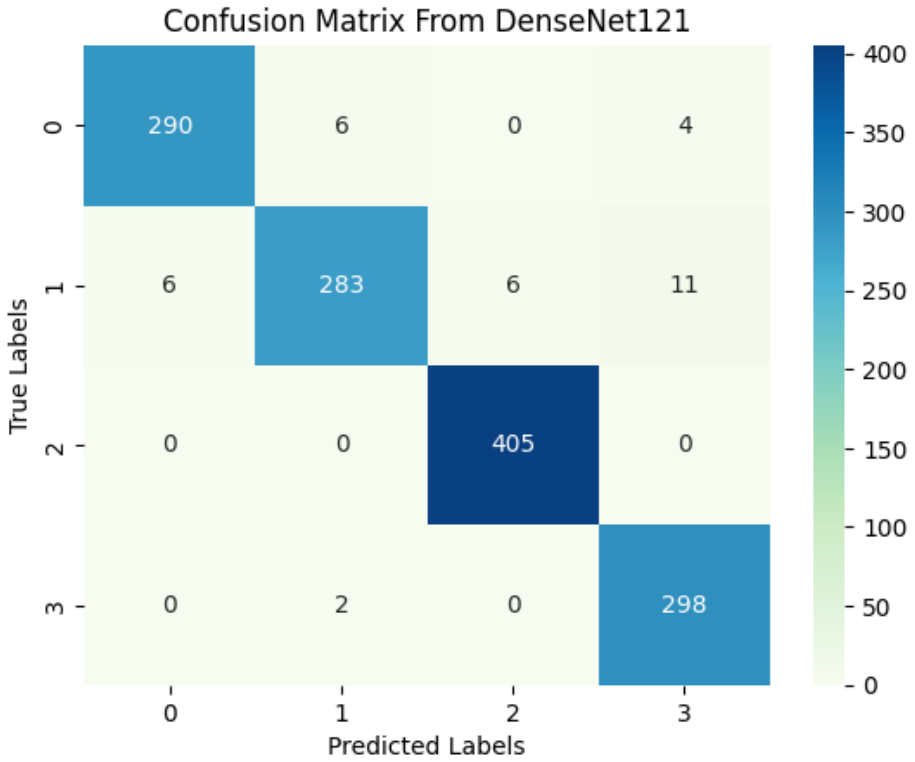

Figure 5.10: Confusion matrix DenseNet121

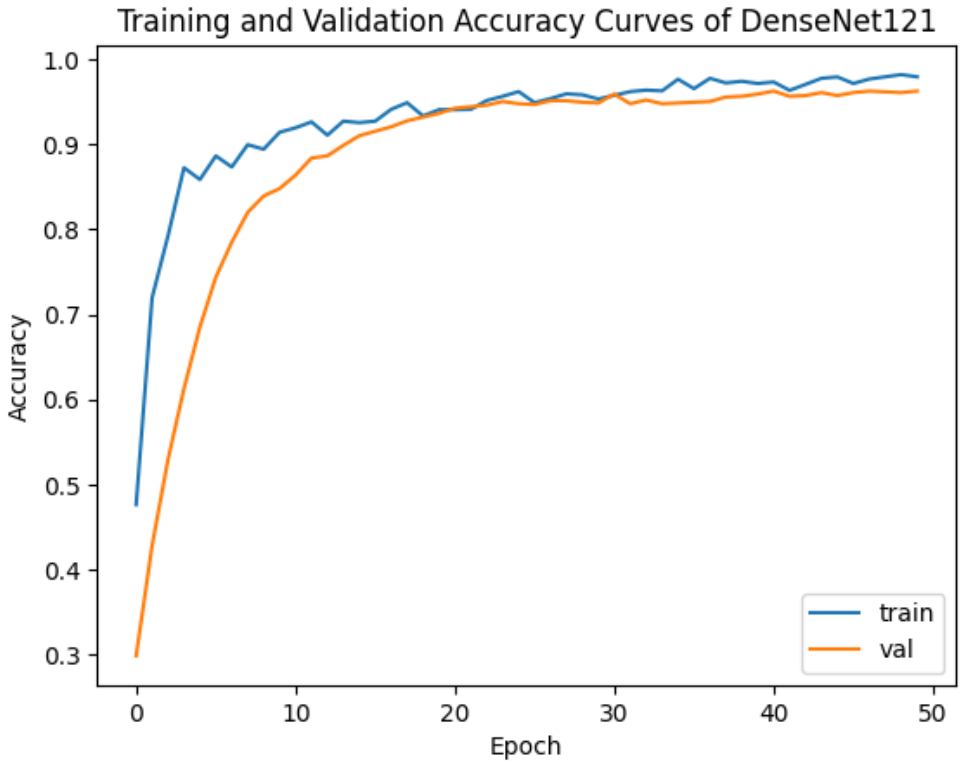

Figure 5.11: Training and Validation accuracy curves DenseNet121

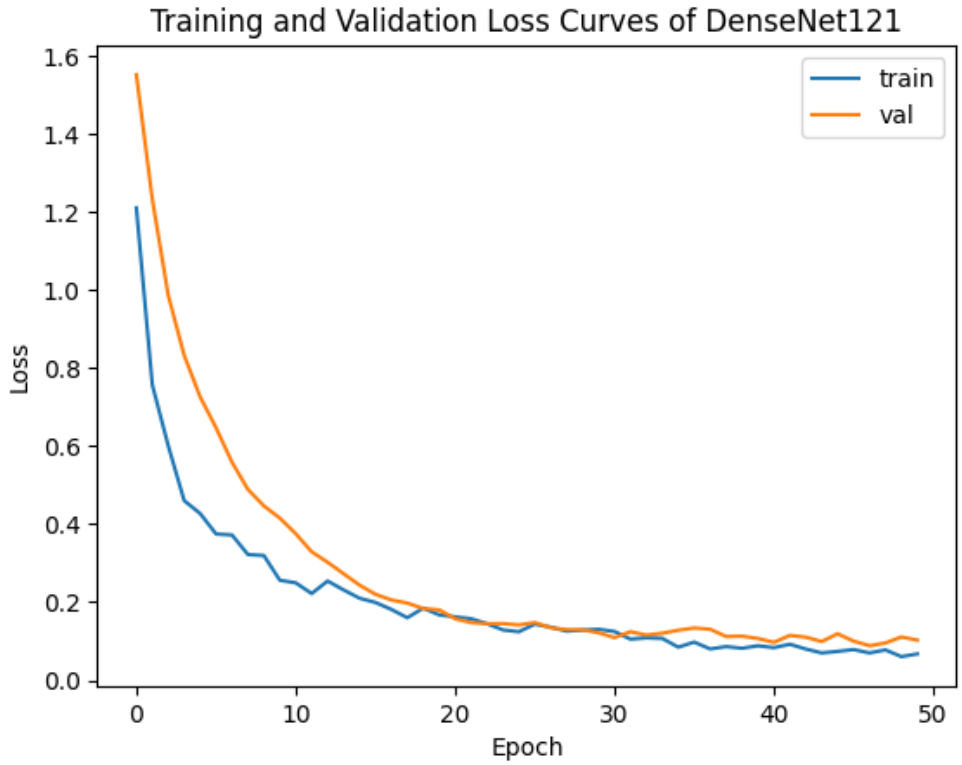

Figure 5.12: Training and Validation loss curves DenseNet121

Class	precision	Recall	f1-score
Glioma	0.98	0.97	0.97
Meningioma	0.97	0.92	0.95
Notumor	0.99	1.00	0.99
Pituitary	0.95	0.99	0.97

Table 5.4: The Precision, Recall and F1-score of DenseNet121

5.5 Ensembling Predictions Through Mean

In this strategy, we have used averaging of the prediction from different convolutional neural network models to get a better prediction. To elaborate, every convolutional neural network model we have used has a dense layer as the output layer. For this experiment, this dense layer has four neural units as the final output layer. Here, we get a 1D matrix of dimension depending on the classes and the shape of the matrix is 1×4. Now, every model gives us a prediction for every class of a number between 0 and 1 as we have used softmax as the activation function.

Now, we have calculated the mean of the prediction of every model for each class and give the final prediction. This strategy gave us an accuracy of 98.32%. We have incorporated a figure[5.13] resembling the whole process. Also, we have incorporated another table[5.5] below showing the precision, recall and f1-score of every class.

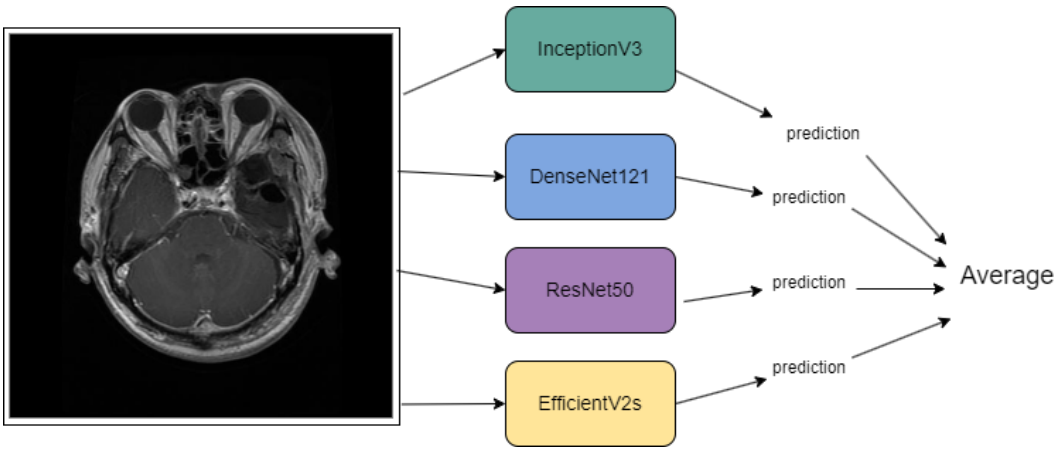

Figure 5.13: Ensemble through Mean Predictions

Class	precision	Recall	f1-score
Glioma	0.99	0.98	0.99
Meningioma	0.98	0.95	0.97
Notumor	0.99	1.00	0.99
Pituitary	0.97	1.00	0.98

Table 5.5: After ensembling the precision, recall and f1-score

5.6 Combining Features Through KNN

In this strategy, we have combined four different convolutional neural network models and the KNN algorithm, which is a machine learning algorithm used in classification problems. To elaborate, we have added the validation dataset to the training dataset that made a new dataset to work with. After that, we have removed the dense layer from the convolutional neural network models. This was done to remove the predictions of the four classes and the to obtain the extracted features from the global average pooling layer of the convolutional neural network models. This global average pooling layer gives us feature extracted output of an array of 1D that we can use with the KNN algorithm. So, ResNet50, EfficientNetV2S, DenseNet121, InceptionV3 the four convolutional neural network models gave us feature extracted output of shape 1×1×2048, 1×1×1280, 1×1×1024, 1×1×2048 for every image in sequential order.

Furthermore, we have combined the extracted features that we got from the four models and the output size became 1×1×6400. Now, we have fitted the combined feature extracted output of every image in KNN algorithm along with their labels. Also, we have set the neighbor to 1. Now for the prediction part, we have loaded the testing dataset into the four convolutional neural network, and they gave us feature extracted output of every image and fitted into the KNN algorithm for prediction. Finally, KNN algorithm gave us an accuracy of 99.38% which is the highest accuracy we have achieved. We have incorporated a figure[5.14] showing confusion matrix and a table[5.6] showing precision, recall and f1-score.

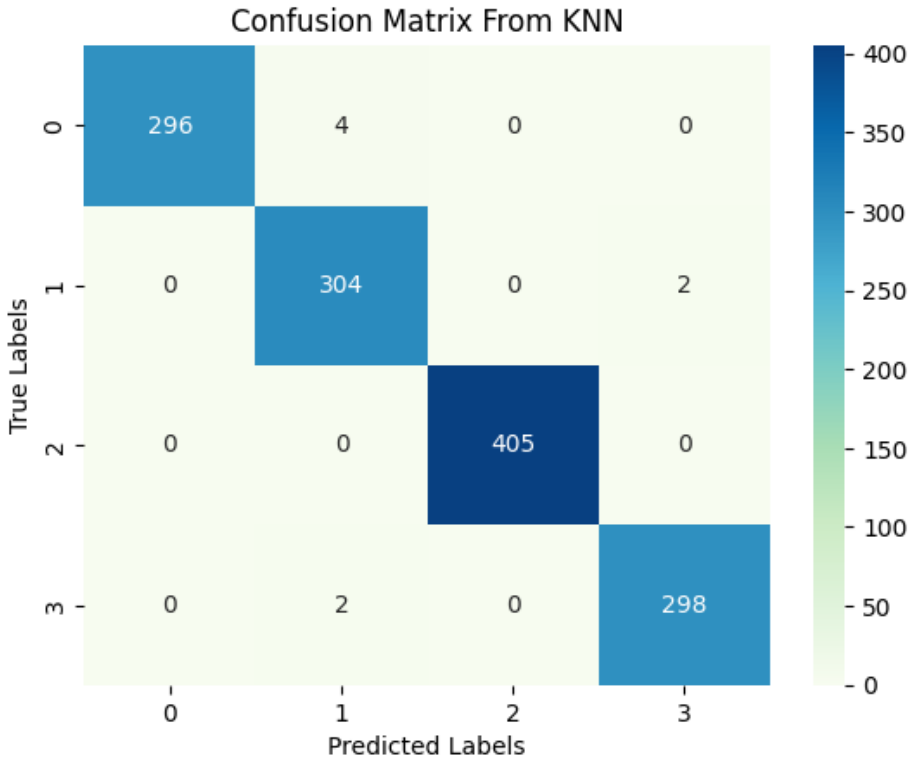

Figure 5.14: Confusion matrix KNN

Class	precision	Recall	f1-score
Glioma	0.99	1.00	0.99
Meningioma	0.99	0.98	0.99
Notumor	1.00	1.00	1.00
Pituitary	0.99	0.99	0.99

Table 5.6: The Precision, Recall and F1-score of KNN

5.7 Comparison Between Results

Here, we have shown a table[5.7] below comparing the accuracy between our CNN models, mean prediction and KNN algorithm. We can see that the best accuracy we have achieved is 99.33% which is predicted from the KNN algorithm. Moreover, the lowest accuracy we have got is 96.41% which is predicted from InceptionV3. Furthermore, our best performing model is 97.55% which is predicted from ResNet50. Also, we have achieved an accuracy of 98.32% from mean prediction ensembling which is the second-best accuracy we have got.

Models	Accuracy	Precision	Recall	F1-score
ResNet50	97.55%	0.98	0.98	0.98
EfficientNetV2S	97.10%	0.97	0.97	0.97
InceptionV3	96.41%	0.96	0.96	0.96
DenseNet121	97.33%	0.97	0.97	0.97
Ensemble prediction	98.32%	0.98	0.98	0.98
KNN	**99.38%**	**0.99**	**0.99**	**0.99**

Table 5.7: Comparison between models and algorithms

5.8 Comparison With Other Papers

Here, we have shown a comparison table[5.8] that shows us a comparison of accuracy between our work and other's work. Here, every work that we have shared in the table used the same dataset that we have used, but their working procedure is different from ours. Now we can see that, our accuracy is the best among other's.

Paper	Techniques	Accuracy
Mingzhe Hu,2023[23]	Grapher Module and an FFN Module	94.89%
Antonius Fajar Adinegoro,2023[24]	CNN	95%
Md Harun or Rashid,2022[25]	CNN	98.43%
Natalija Ivoš,2022[26]	Fine-Tuned transfer learning	97%
Our work	**CNN and KNN**	**99.38%**

Table 5.8: Comparison with other papers

Chapter 6

Conclusion

Deep learning is the newest and one of the most powerful methods in the machine learning field that gave researchers much better results to find a feasible solution for complex real-world problems. The goal of this study was to examine the problem of a major, life-threatening medical emergency and see how using deep learning in this area could help healthcare professionals make a better and more accurate clinical diagnosis.

We applied convolutional neural networks: Resnet50, DenseNet121, Ef- ficient-NetV2S, InceptionV3 to classify brain tumors into glioma, meningioma, and pituitary classes using brain tumor MRI dataset. We tried to find better accuracy through pre-processing, training, validating, testing, combining extracted features, averaging probabilities, using KNN machine learning algorithm.

We have achieved 99.38% accuracy, and we aim to fine-tune our experiments for better results. In the grand scheme of the universe, we hope that this study will give next-generation researchers a foundation to start their research journey.

Bibliography

[1] H. Mohsen, *Classification using deep learning neural networks for brain tumors.* 2018.

[2] J. A. K. N.Ullah, *An effective approach to detect and identify brain tumors using transfer learning.* 2022.

[3] Ö. F, *Brain tumor detection based on convolutional neural network with neutrosophic expert maximum fuzzy sure entropy.* 2019.

[4] Akbani, *Brain tumor detection using deep learning.* 2022.

[5] M. M. Arkapravo Chattopadhyay, *Mri-based brain tumour image detection using cnn based deep learning method.* 2022.

[6] S. K. M.Sajjad, *Multi-grade brain tumor classification using deep cnn with extensive data augmentation.* 2019.

[7] P. M. P Gokila Brindha M Kavinraj and P. Prasanth, *Brain tumor detection from mri images using deep learning techniques.* 2021.

[8] P. P. Ankita Parmar Mehfuza Holia, *A survey on brain tumor detection using deep learning.* 2020.

[9] M. A.Gumaei, *A hybrid feature extraction method with regularized extreme learning machine for brain tumor classification*, 2019.

[10] S. Sajid, *Brain tumor detection and segmentation in mr images using deep learning.* 2019.

[11] C. Marosi, M. Hassler, K. Roessler, *et al.*, "Meningioma," *Critical Reviews in Oncology/Hematology*, vol. 67, no. 2, pp. 153–171, 2008, ISSN: 1040-8428. DOI: https://doi.org/10.1016/j.critrevonc.2008.01.010. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S104084280800022X.

[12] K. Lamszus, *Journal of neuropathology and experimental neurology,* 2004.

[13] A. Zbiciak and T. Markiewicz, "A new extraordinary means of appeal in the polish criminal procedure: The basic principles of a fair trial and a complaint against a cassatory judgment," en, *Access to Justice in Eastern Europe*, vol. 6, no. 2, pp. 1–18, Mar. 2023.

[14] A. Pace and A. Pompili, "Depression in patients with high-grade glioma: Results of the glioma project," en, *Neurosurgery*, vol. 56, no. 3, E629, Mar. 2005.

[15] A. P. Amar and M. H. Weiss, *Pituitary anatomy and physiology.* 2003.

[16] A. Kaushik, *Understanding resnet50 architecture*, 2020.

[17] *Papers with Code - ResNet Explained — paperswithcode.com*, https://paperswithcode.com/method/resnet, [Accessed 22-May-2023].

[18] A. Sarkar, *EfficientNetV2—faster, smaller, and higher accuracy than Vision Transformers — towardsdatascience.com*, https://towardsdatascience.com/efficientnetv2-faster-smaller-and-higher-accuracy-than-vision-transformers-98e23587bf04, [Accessed 22-May-2023].

[19] *Architecture of DenseNet-121 — https*, https://iq.opengenus.org/architecture-of-densenet121/, [Accessed 22-May-2023].

[20] *Inception V3 Model Architecture — iq.opengenus.org*, https://iq.opengenus.org/inception-v3-model-architecture/, [Accessed 22-May-2023].

[21] Q. Kuang and L. Zhao, *A practical gpu based knn algorithm.* 2009.

[22] A. Pandey and A. Jain, *Comparative analysis of knn algorithm using various normalization techniques.* 2017.

[23] X. Yang, *End-to-end brain tumor detection using a graph-feature-based classifier — spiedigitallibrary.org*, https://www.spiedigitallibrary.org/conference-proceedings-of-spie/12468/124681C/End-to-end-brain-tumor-detection-using-a-graph-feature/10.1117/12.2654020.full?SSO=1, [Accessed 22-May-2023].

[24] A. F. A. a and G. N. S. a, *Classification and segmentation of brain tumor using efficientnet-b7 and u-net*, 2023.

[25] *BrainNet-7: A CNN Model for Diagnosing Brain Tumors from MRI Images based on an Ablation Study - ProQuest — proquest.com*, https://www.proquest.com/openview/44421bad128919eb3377cd5c312b9a31/1?pq-origsite=gscholar&cbl=5444811, [Accessed 22-May-2023].

[26] N. I. 1., *Application of convolutional neural networks for detection and classification of brain tumors*, 2022.