Brain Tumor Detection using Transfer Learning with AlexNet and CNN

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Brain Tumor Detection using Transfer Learning Technique with AlexNet and CNN

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Abstract

The segmentation, identification, and extraction of malignant tumor areas from magnetic resonance (MR) images is a major issue, yet it's a monotonous and long-term operation that radiologists or clinical specialists must undertake, and their accuracy is entirely reliant on their experience. As a result, the deployment of computer-assisted technology becomes more important to overcome these obstacles. Numerous researchers have proposed several approaches for accurate brain tumor identification and segmentation. A comparison of several procedures has been conducted. After a detailed analysis, Image Rejuvenate and Intensification are revealed to be two major issues which are resolved and explained using appropriate methodologies. In this paper, Convolutional Neural Network (CNN) and AlexNet have been implemented to increase the performance and minimize the complexity involved in the magnetic resonance image segmentation process. Secondly, important features are retrieved from segmented tissues to increase the accuracy and performance efficiency using support vector machine (SVM) - histogram of oriented gradient (HOG). Based on accuracy, precision matrix, and confusion matrix, the experimental outcome of the proposed methodology have been verified and evaluated for quality assurance and efficiency on MR images. The research results proved to be 97% accurate indicating the hypothesized methods for detecting healthy and cancerous tissues.

1 Introduction

The term "brain tumor" refers to an abnormally growing lump of brain cells which can cause significant damage to the nervous system. Early detection of brain tumors may vastly boost the patients' potential treatments and survival rates. Despite this, manual tumor categorization utilizing many MRI images generated in medical practice is a time-consuming and labour-intensive job. MRI scans are significant around automatic medical analysis because they help see distinct brain structures and provide extensive information about them. Using MRI scans, scientists have tried several approaches for identifying and categorizing brain tumors. These papers include a range from traditional medical image processing to modern machine learning techniques.

Machine learning (ML) approaches were formerly assumed to provide the foundation for automating categorization and mining activities. Nowadays, researchers have been encouraged to look for novel techniques of brain tumor detection to enhance classification accuracy due to the lack of accuracy in prediction techniques and the vital role of medical data analysis. As a result, transfer learning has risen to prominence due to its ability to create accurate prediction models utilizing large amounts of datasets. Transfer learning is widely used to identify affected areas of the brain, as well as to categorize pictures and forecast models Nazir et al. (2021). The efficiency of prediction methods and statistical analysis using transfer learning models is largely dependent on data collection and its training, as good results require reliable information.

A novel approach to diagnose a brain tumor using AlexNet at a preliminary phase for better medication. Before a brain tumor is detected medically, a radiological examination is necessary to assess its location, size, and influence on the outlying areas. The symptoms of a brain tumor noticed by MR scans. Sometimes it is hard to conclude that it is a healthy blood cloth or a brain with a tumor. The difference between both is shown in Figure 1. Because the tumor is not always clearly visible in MRI, it might be difficult to detect it. MRI is a more efficient type of imaging than X-ray. MR scans do not produce harmful radiation. It also gives the required information to the doctors for diagnosis and to treat illnesses. To identify and diagnose brain cancers, MR images are pre-processed. Depending on the demands, several types of MRI are utilized in this procedure.

The benefit of using pre-trained model is it saves time because it does not require a big data collection to provide results. For segmentation, these models extracted arbitrary characteristics from MR images. The proposed methodology makes a significant contribution by converting the input MR images into a single channel. The Augmentation technique is used to better segment and clarify the tumor area. Deep features (CNN and AlexNet) and histogram orientation gradient (HOG) - support vector machine (SVM) was retrieved and merged in a single feature extraction for differentiating tumors from normal images during the classification phase.

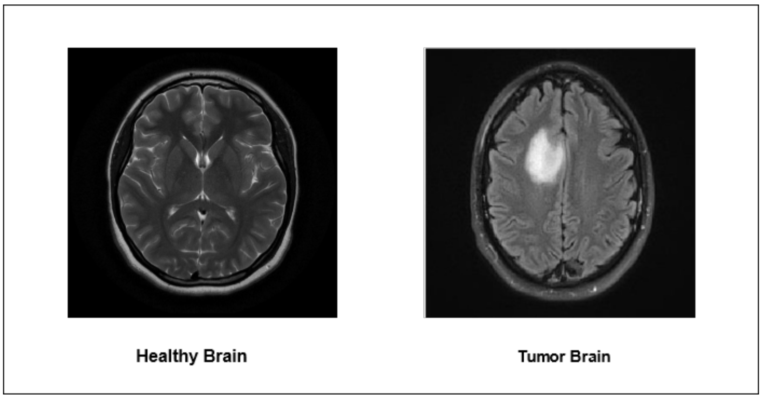

Figure 1: Difference between tumor and non tumor brain

Research Question

"How efficiently can Transfer Learning be used to accurately detect brain tumor and minimize the processing time?"

Keywords: ***Transfer Learning, Convolutional Neural Network(CNN), Feature Extraction, AlexNet, Support Vector Machine, Histogram of Gradient, Magnetic resonance imaging (MRI)***

2 Related Work

Since the last few decades, brain tumor diagnosis using MRI image classification has gotten a lot of support from researchers. One of the research areas that is gaining traction is medical image processing. Many studies have applied algorithms and techniques to the segmentation of medical images. The scientists used a variety of techniques to improve the identification of brain tumors to diagnose and classify. Some of them are mentioned below.

Biswas and Islam (2021) provided a tumor categorization utilizing K-mean, ANN, and Principal Component Algorithms as well as other machine learning approaches (PCA). They utilized the k-mean technique to pre-process the data from brain tumor pictures. This study discovered 95.4% accuracy, 94.58 % sensitivity, and 97.83% specificity. Padmapriya et al. (2021) discussed BTC convolution neural network images after extensive experiments utilizing transfer learning but without record expansion. In this research, the authors present a thorough examination of previously completed surveys as well as BTC's most recent deep learning techniques. Sejuti and Islam (2021) suggested that a solution based on CNN and SVM correctly identify brain tumors. Applying the CNN model to extract features, and apply another predictor named the support vector machine to improve the CNN model's accuracy. M (2021) MRI (Magnetic Resonance Imaging) is a commonly used medical imaging tool to classify and assess the stage of these tumors. This research presents an automatic segmentation method based on CNN (Convolutional Neural Networks). Furthermore, M (2021) noted that using a depth normalization approach as a pre-processing technique, which isn't commonly used in CNN-based segmentation but has been found to be very accurate for brain tumor segmentation in MRI images when paired with data augmentation. Deepa et al. (2021) Providing feedback on the efficacy of a CAD device in identifying MRI structural abnormalities is a tough task. A novel CAD device approach for detecting brain structural abnormalities such as malignancies has been proposed as a solution to this problem. The feature extraction approach, as well as PNN as a classifier, provide the best outcomes as compared to RBF, BPN, HNN, and RNN in MRI images by 16.71%, 18.76%, 19.00%, and 21.15%, respectively. Arbane et al. (2021) described a method for identifying brain cancers from MRI scans automatically. The method is based on transfer learning and is implemented using three CNN architectures. Considering the amazing sample size, the results showed that pre-trained deep learning models may be effectively utilized to build a classifier capable of detecting tumor in brain MRIs. In terms of precision, accuracy and F1-score, the MobilNet-v2 deep learning model beat both other models. The research paper of Shahajad et al. (2021) determines if the brain tumor is normal or abnormal. They utilized 90 healthy MRI pictures and 154 images having tumor MRI images from the Kaggle dataset. It has been discovered that as the selection of attributes increases, the accuracy of the SVM classifier increases. At 6-7 characteristics, the investigation accuracy of around 92% is achieved. The paper Bhanothu et al. (2020) addresses the application of a deep learning system to automatically detect and categorize tumor in MR images. The Faster R-CNN method was utilized to detect tumor areas and classify them as glioma, meningioma, or pituitary tumor. The suggested method efficiently identifies brain tumor areas by selecting the optimal bounding box produced by RPN. A clearer MAP was produced to detect brain tumor based on the test dataset.

As per Huang et al. (2020) the network pattern is developed using randomly chosen graph algorithms. These randomly chosen graphs are mapped into a computable neural network via a network generator. The classification accuracy of the revised CNNBCN model is 95.49%, which is greater than many other models used in prior research. This is preferable than several other hypothesis that have been explored in previous publications. Additionally, when compared to the ResNet, DenseNet, and MobileNet versions, the improved CNNBCN model has a reduced failed test of tumor classification.

Irsheidat and Duwairi (2020) have developed a model to analyse magnetic resonance images using mathematical formulae and matrix operations utilizing Artificial Convolutional Neural Networks. In this research, proposed model is able to increase size by 14 times via data augmentation. With 96.7% accuracy in validation data and approximately 88.25% accuracy in test cases, the model predicted the existence of a tumor.

Nadeem et al. (2020) the goal is to examine important deep learning issues related to brain tumor research using the wide range of applications of deep learning (e.g., segmentation, classification, prediction, and assessment). This publication provides a high-level summary of many scientific contributions to the subject.

Noreen et al. (2020) compared two different instances that were assessed using a pre-trained DenseNet201 machine learning model, the features were extracted from multiple DenseNet blocks. These features were then combined and passed to the softmax classifier to detect the brain tumor. Features from multiple Convolution layers were retrieved, concatenated, and passed to the softmax for classification of brain tumor using a pre-trained Inception-v3 model. All scenarios were tested using a publicly available three-class brain tumor database.

Choudhury et al. (2020) summarizes deep learning algorithms, particularly CNN and have demonstrated amazing effectiveness in bioinformatics, but owing to a variety of intrinsic difficulties, only a few techniques have been applied. CNN, sometimes referred to as ConvNet, is a deep machine learning method for video analysis. The model obtains an overall accuracy of 96.08%.

Derea et al. (2019) shows how the threshold value affects the segmentation of brain MRI images at various levels such as normal, benign, and malignant. They used GLRLM technique. By separating the tumor from the complement region, the texture features generated by GRLM have a high level of accuracy. Shahriar Sazzad et al. (2019) revealed the higher accuracy of brain tumor identification, which included augmentation to decrease Gray-scale colour fluctuations. A filter process was performed to remove as much unwanted noise as possible to help enhance segmentation. The testing results revealed that the suggested technique was able to obtain better precision outcomes. Zulkoffli and Shariff (2019) utilized a region-growing method to detect brain tumours on MRI images. The Support Vector Machine detects the tumor region by combining k-means clustering and morphological segmentation approaches. The skull and other unwanted artifacts are removed from the image, as well as the tumor is processed to get accurate classification data. Zaw et al. (2019) described the method developed will accurately identify the tumor anywhere in the brain, including temporal lobe (that aligns with the eye level). The system has an accuracy rate of 94% and a diagnosis score of 81.25% on tumor scans and 100% on non-tumor scans. According to Deepak and Ameer (2019), transfer learning appears to be a good approach for reducing the supply of medical scans. The study includes the area under the curve (AUC), accuracy, recall, F-score, and specificity. Additionally, the study explores a functional component by evaluating the technique with less training sets. Experiments of Ismael and Abdel-Qader (2018) demonstrate that the feature extraction method is accurate, and it can produce a useful feature set that may be utilized to increase performance when combined with some other classification algorithms. Mohan and Subashini (2018) aims to reflect back on recent advances in tumor-infected brain MR image segmentation and classification, with an emphasis on gliomas such as astrocytoma. The procedures for removing and grading tumours have been described. According to Chen et al. (2017), accurate and generalized segmentation of brain tumours remains a problem due to the complex characteristics of brain tumours in magnetic resonance imaging. To overcome this problem, they proposed a novel technique for brain tumor segmentation built on segregated local square characteristics.

Table 1: Comparison of Reviewed Articles

Author	Objectives	Algorithms	Results
Mohd Shahajad, Deepak Gambhir, and Rashmi Gandhi	Feature extraction for classification of brain tumor MRI images using support vector machine	SVM	An accuracy of nearly 92% is achieved with an increase in number of features, then the accuracy stagnates.
Muhammad Waqas Nadeem, Mohammed A. Al Ghamdi, Muzammil Hussain, Muhammad Adnan Khan, Khalid Masood Khan, Sultan H. Almotiri and Suhail Ashfaq Butt	Brain Tumor Analysis Empowered with Deep Learning: A Review, Taxonomy, and Future Challenges	Deep Learning Methods	Disappointingly, there were no clear techniques or methods to assess the best set of hyper-parameters for empirical exercise.
Neelum Noreen, Sellappan Palaniappan, Abdul Qayyum, Iftikhar Ahmad, Muhammad Imran and Muhammad Shoai	A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor	DenseNet201 deep learning model and Inception-v3 model	The proposed method achieved the highest performance in detection of brain tumor.
Yakub Bhanothu, Anandhanarayanan Kamalakannan, Govindaraj Rajamanickam	Detection and Classification of Brain Tumor in MRI Images using Deep Convolutional Network	Region Proposal Network (RPN), VGG-16	As a performance measure, the algorithm achieved a mean average precision of 77.60% for all the classes.
Zhiguan Huang, Xiaohao Du, Liangming Chen, Yuhe L, Mei Liu, Yao Chou, Long Jin	Convolutional Neural Network Based on Complex Networks for Brain Tumor Image Classification With a Modified Activation Function	modified CNNBCN, ResNet, DenseNet and MobileNet	The result reaches 95.49%.

Table 2: Comparison of Reviewed Articles

Author Results	Year	Objectives	Algorithms
Angona Biswas and Md. Saiful Islam	Brain Tumor Types Classification using K-means Clustering and ANN Approach	K-means clustering, ANN, Feature extraction	This proposed method provides 95.4% accuracy, 94.58% sensitivity, 97.83% specificity.
Zarin Anjuman Sejuti; Md Saiful Islam	An Efficient Method to Classify Brain Tumor using CNN and SVM	Support Vector Machine(SVM), Convolutional Neural Network(CNN)	The final accuracy of this proposed CNN-SVM based method is found 97.1%.
Bhuvaneswari M	Automatic Segmenting Technique of Brain Tumors with Convolutional Neural Networks in MRI Images	Convolutional Neural Networks(CNN)	The ability of significant plans via little sections by differentiating the profound CNN and shallow structures with greater channels were done.
B. Deepa; M.G. Sumithra; R. Mahesh Kumar; M. Suriya	Weiner Filter based Hough Transform and Wavelet feature extraction with Neural Network for Classifying Brain Tumor	HNN, RNN, BPN, PNN	The outcomes implies that on an average, Weiner filter as denoising method, Hough Transform as dissection method, Wavelet Transform as feature extraction method and PNN as a classifier is giving loftier results than RBF classifier by 16.71%, BPN by 18.76%, HNN by 19.00% and RNN by 21.15% in MRI images.
Mohamed Arbane; Rachid Benlamri; Youcef Brik; Mohamed Djerioui	Transfer Learning for Automatic Brain Tumor Classification Using MRI Images	CNN, ResNet, Xception and MobilNet-V2	The best results with 98.24% and 98.42% in term of accuracy and F1-score, respectively.

Table 3: Comparison of Reviewed Articles

Author	Objectives	Algorithms	Results
Aya S Derea, Heba Kh. Abbas, Haidar J. Mohamad, Ali A. Al-Zuky	Development of Automated Brain Tumor Identification Using MRI Images	Segmentation and Feature selection and Feature extraction using GRLM	The detection results were very successful in separating the whole tumor region, based on the segmentation technique used.
Chirodip Lodh Choudhury, Chandrakanta Mahanty, Raghvendra Kumar, Brojo Kishore Mishra	Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network	CNN, DNN	he model captures a mean accuracy score of 96.08% with fscore of 97.3%
Suhib Irsheidat, R. Duwairi	Brain Tumor Detection Using Artificial Convolutional Neural Networks	CNN	The model gave us excellent results of predicting the existence of a tumor which reached 96.7% in validation data and up to 88.25% on test data.
T. M. Shahriar Sazzad, K. M. Tanzibul Ahmmed, Misbah Ul Hoque, Mahmuda Rahman	Development of Automated Brain Tumor Identification Using MRI Images	Segmentation and Feature selection	This research study proposed approach reduces time and provides higher accuracy compared to other existing approaches
Hein Tun Zaw, Noppadol Maneerat, Khin Yadanar Win	Brain tumor detection based on Naive Bayes	Naive Bayes, Feature extraction	With an average accuracy of 94%, this approach develops an 81.25% detection rate on tumor images and a 100% detection rate on non-tumor images.

Table 4: Comparison of Reviewed Articles

Author	Objectives	Algorithms	Results
S.Deepak P.M.Ameer	Brain tumor classification using deep CNN features via transfer learning	Deep transfer learning and GoogLeNet	The proposed system records a mean classification accuracy of 98%, outperforming all state-of-the-art methods.
Zuliani Zulkoffli, Talha Afzal Shariff	Detection of Brain Tumor and Extraction of Features in MRI Images Using K-means Clustering and Morphological Operations	K-mean clustering, morphological segmentation and Feature Extraction	The proposed method has given good results and accuracy.
S. Somasundaram; R. Gobinath	Current Trends on Deep Learning Models for Brain Tumor Segmentation and Detection – A Review	CNN, ANN, SVM and Multi-class Support vector machines (MCSVM)	This article implying about present status on segmentation and Detection of tumor-based image processing through deep learning models.
Wei Chen, Xu Qiao, Boqiang Liu, Xianying Qi, Rui Wang, Xiaoya Wang	Automatic brain tumor segmentation based on features of separated local square	superpixel-wise features and SVM	The final goal is to develop a CAD system that can distinguish the benign tumor and malignant tumor.
Mustafa R. Ismael, Ikhlas Abdel-Qader	Brain Tumor Classification via Statistical Features and Back-Propagation Neural Network	2D Discrete Wavelet Transform (DWT) and 2D Gabor filter techniques	The proposed method obtained a total accuracy of 91.9%, and specificity of 96%, 96.29%, and 95.66% for Meningioma, Glioma, and Pituitary tumor respectively. .

3 Methodology

This study focused on an automated gadget that can aid doctors in diagnosing and improving survival rates. Detecting brain tumours physically is time-consuming and ineffective, so deploying an automated system might be a game-changer. As stated in related research, deep learning is a very effective module for identifying brain cancers. Increasing revenue growth and inventiveness have been attributed to decision-making analysis of data acquired from numerous sources. This research uses the CRISPDM

(Cross Industry Standard Process for Data Mining) data analysis technique to diagnose a brain tumor. Figure 2 depicts the mechanism workflow for the research method, which comprises comparable actions performed during the study.

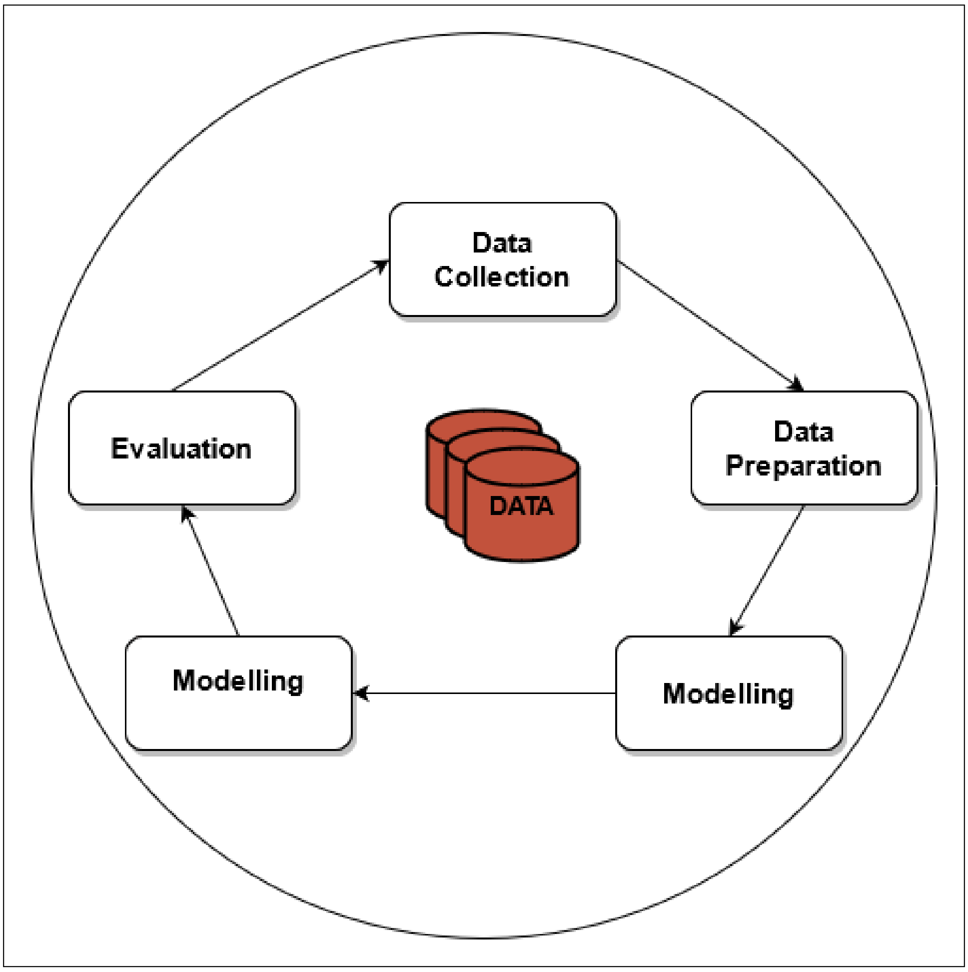

Figure 2: Working of CRISPDM

3.1 Data Collection

This paper is based on the dataset Brain MRI Images for Brain Tumor Detection [1]. One of the most challenging issues in medical imaging research is segmenting neurological disorders from comprehensive imaging data since clots vary in size and type. As shown in Figure 3, Brain MR scans were utilized to collect evidence and the images in the data have been manually labelled by specialists and skilled neurologists. It also shows a division of sub-regions: glioma tumor, meningioma tumor, and pituitary tumor, which are all fused together. The cluster of 3 images named Tumor in Figure 3 shows tumor formations of various modalities.

[1]https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection

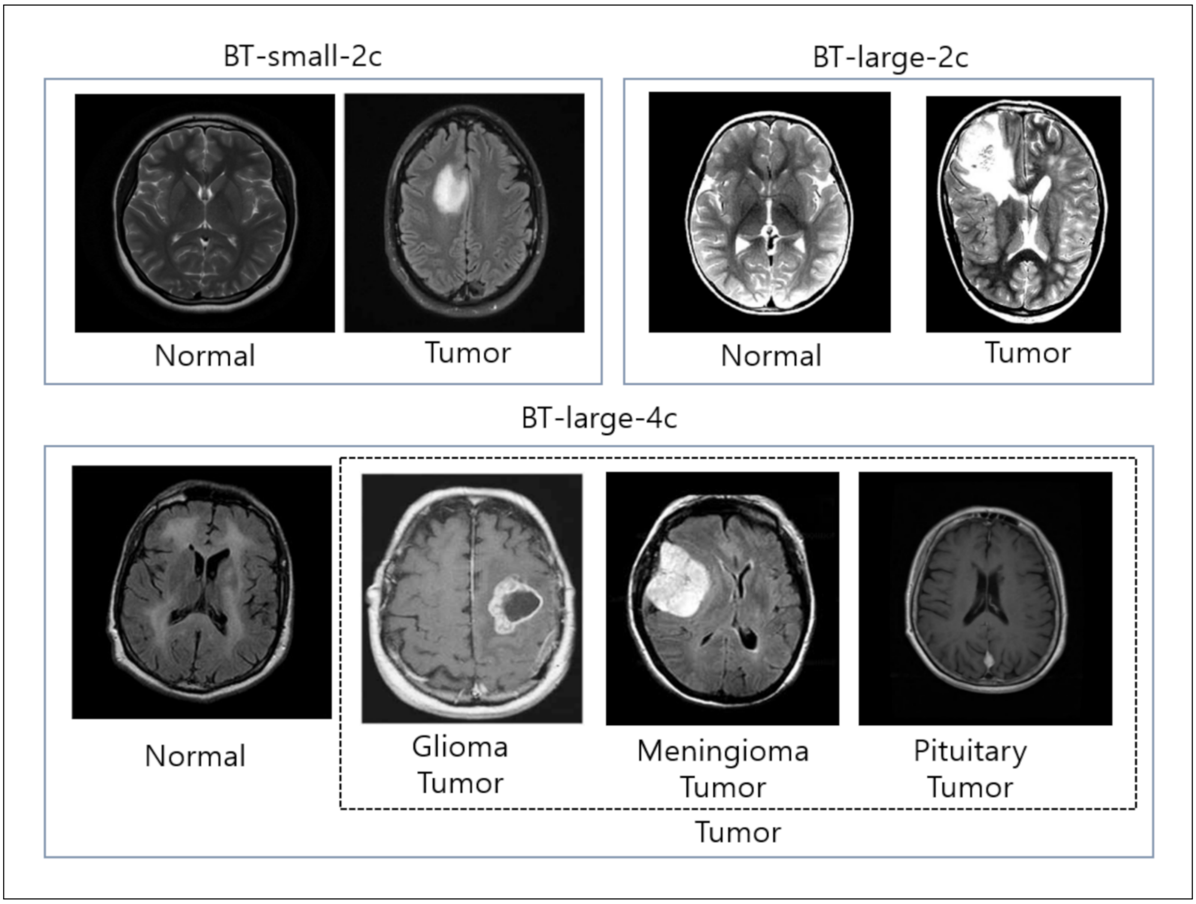

Figure 3: Types of Tumor

3.2 Data Preprocessing

Image Augmentation, libraries of Keras and Tenserflow are used to determine the same size for all the data, which allow the model to be more generalized and accurate. Using Augmentation method, dataset is enhanced with a number of random modifications (rotations, height and width shifts, brightness changes, and so on). The settings for data augmentation procedures are chosen so that the suggested classifier never sees the same image again. This method improves the model's generalization and prevents overfitting as shown in Figure 4.

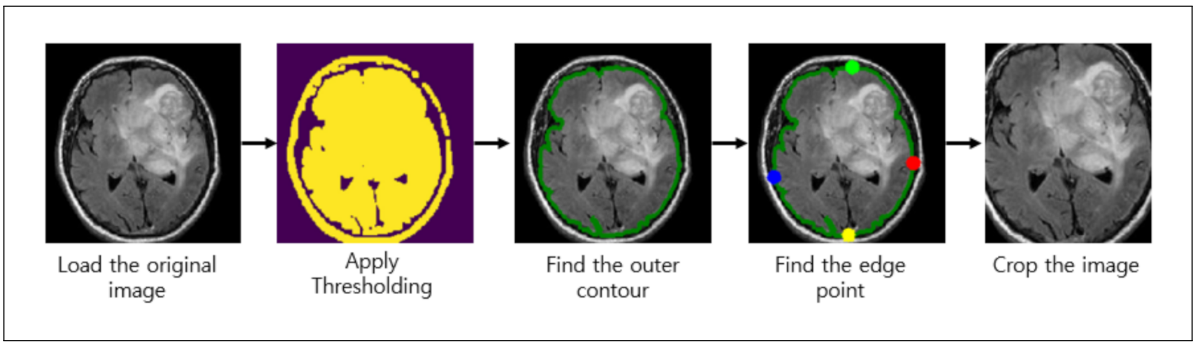

Figure 4: Process of augmentation

The initial objective in this phase is to use a similar method with the one to crop the brain tumor out of image backdrop. The goal of this approach is to find the enclosed box's extreme points. As a result, the brain contour is recovered from a cropped picture by finding the x and y coordinates including its upper, lower, left, and right end points, as illustrated in Figure 5.

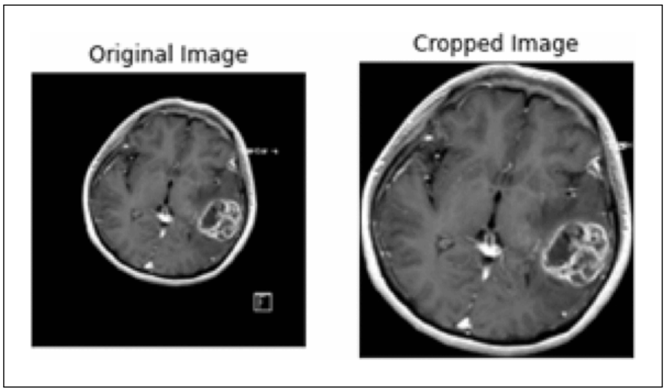

Figure 5: Process of Image Cropping

3.3 Modeling

3.3.1 Convolutional Neural Network (CNN)

In the world of clinical image processing, Convolutional Neural Networks are widely applied. Many experts have tried numerous times to develop a model that can detect tumours more accurately. This research attempted to develop a model that can reliably diagnose tumors from 2D brain MRI scans. Although a deep Convolutional Neural Network may identify the tumor, the chosen CNN model has parameters such as pooling and connection dimensionality.

For brain tumor detection, five-layer Convolutional Neural Network is deployed. This proposed model, which consists of seven phases and includes the hidden layers, gives us the most noticeable result for tumor detection.

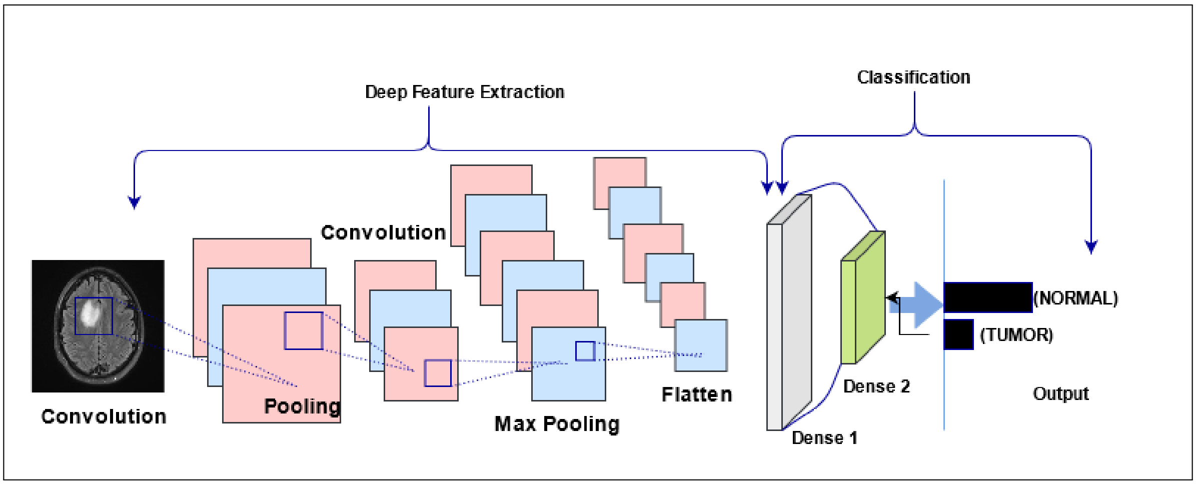

Figure 6: Working of CNN in this research

In Figure 6, the spatial scale of the visualization in CNN architecture is decreased to reduce the amount of data as well as the network's processing time. Focusing on MRI image can lead to contamination of overfitting, as well as the Max Pooling layer is ideal for this scenario. The research utilizes Max Pooling 2D to model geographical data that appears to confirm with input image.

A max pooling map is created when the pooling layer is applied. After pooling, the most important layers are flattening, because it needs to convert the entire matrix containing the input images together into single column vector, which is necessary for processing. The data is subsequently sent into the Neural Network, which is used for processing. Dense-1 and Dense-2 are the two core dense layers used. In Keras, the dense method helps to analyse the Neural Network, and the resulting vector is used as an input for this layer.

The hidden layer contains 128 nodes. As its dimensionality or nodes is equivalent to the computational resources, it is needed to fit the proposed model. It is kept as low as feasible, and 128 nodes provides the most significant outcome in this case. In the activation function, the ReLU is utilised for its superior convergence performance. After the initial dense layer, the second completely connected layer has been deployed as the model's last layer. A sigmoid function is selected as an activation function in this layer, with a total number of nodes of one, because of the need to reduce the usage of computational resources so that a larger amount of time could be saved.

3.3.2 AlexNet

AlexNet is an uncommon strong model that can achieve high levels of accuracy on even the most challenging datasets. Function of AlexNet could be severely harmed if any of convolutional layers are removed. AlexNet is a dominant architecture for any element detection, and it might have a variety of features in the machine learning field of computer vision. In the near future, AlexNet could be used for image processing tasks more than CNNs.

AlexNet is made up of 5 fully linked layers and 3 convolutional layers. Convolutional Kernels , also known as filters extract important characteristics from the given image dataset. The outcome of the 5th convolutional layer is fed into a sequence of 2 fully connected layers through an Overlapping Max Pooling layer. AlexNet enables for multi-GPU development by taking half of a model's brains on one single GPU and the remaining half on another GPU. This not only allows for the training of a larger size model, but it also reduces the preparation time. The workflow of AlexNet model shows in Figure 7[2] below:

[2]https://learnopencv.com/understanding-alexnet/

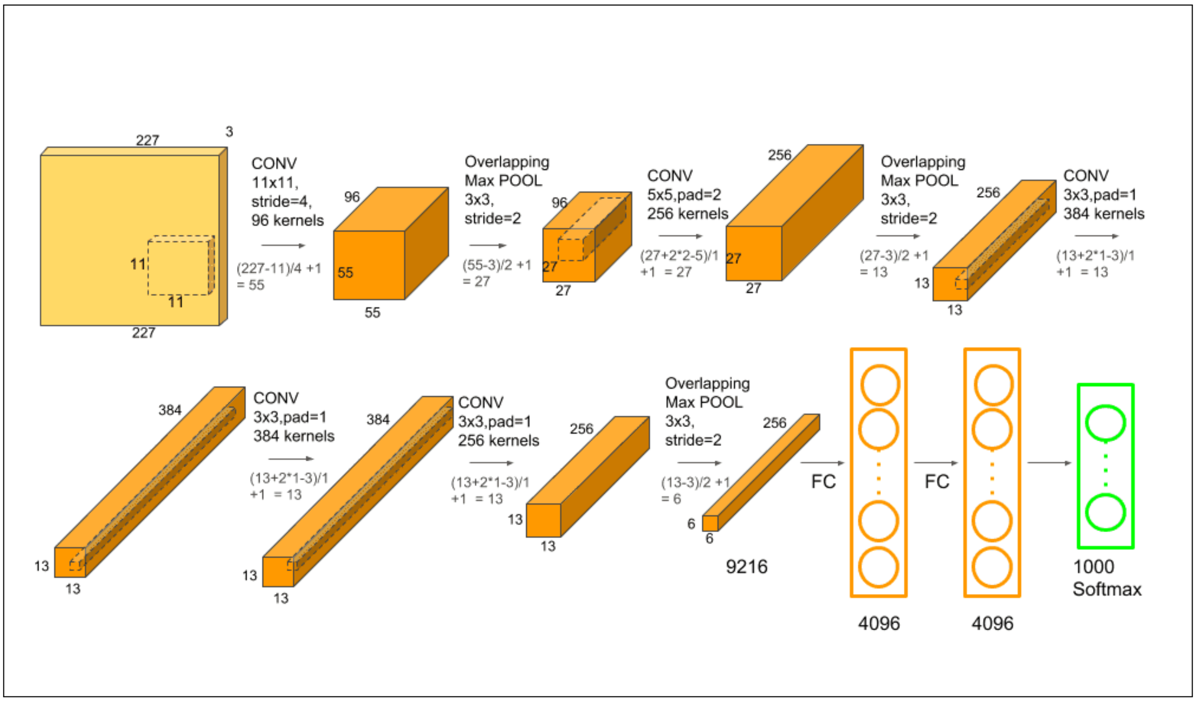

Figure 7: Architecture of AlexNet

3.3.3 Support Vector Machine (SVM)- Histogram of Oriented Gradients (HOG)

The Support Vector Machine, or SVM, is a linear model that may be used to solve classification issues. It can handle both linear and nonlinear problems and is useful for a wide range of applications. SVM is a basic concept: The method divides the data into categories by connecting the dots or hyperplane. The statistical learning theory underlies the SVM. They should be used to study how to forecast information in the future. Solving a restricted quadratic optimization problem is used to train the SVM. SVM[3] employs a collection of nonlinear kernel function to transform inputs into a high-dimensional space.

Histogram of Oriented Gradients (HOG) is a feature extraction technique that is used in image processing to recognize objects. The aim of a feature descriptor is to generalize an item in a picture so that it provides the same features extracted in pictures containing that object taken under various situations such as perspective, lighting, location. The HOG descriptor approach counts frequencies of gradient orientation inside an image pixel, or region of interest, in a specific area of an image (ROI).Figure 8

[3] https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example-code/

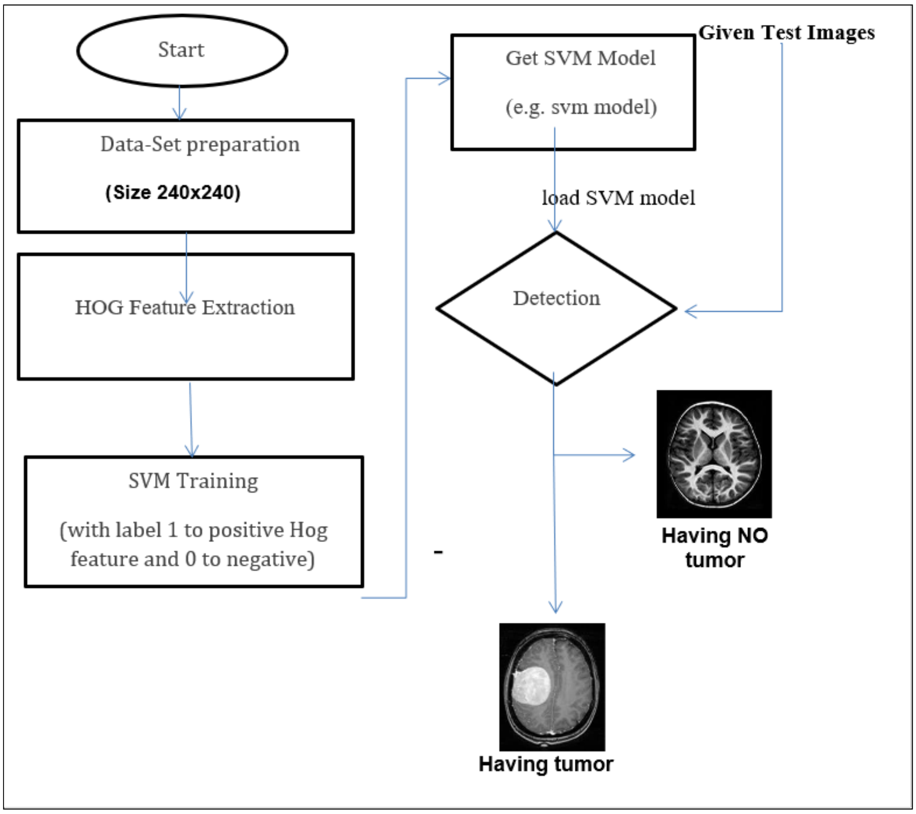

Figure 8: Procedure of SVM+HOG

3.3.4 Pre-Trained Models for Feature Extraction

The feature extraction tool is utilized to produce parameters that identify the tumor by Filter Median approach. This portion output is sent into the thresh keeping procedure in its entirety, as well as the mask is applied repeatedly over the whole picture. It highlights the fact that black pixels are darker and white pixels are lighter. Whenever an algorithm's data set is too vast to analyze and is suspicious of being redundant, it can be decreased to a smaller collection of features.

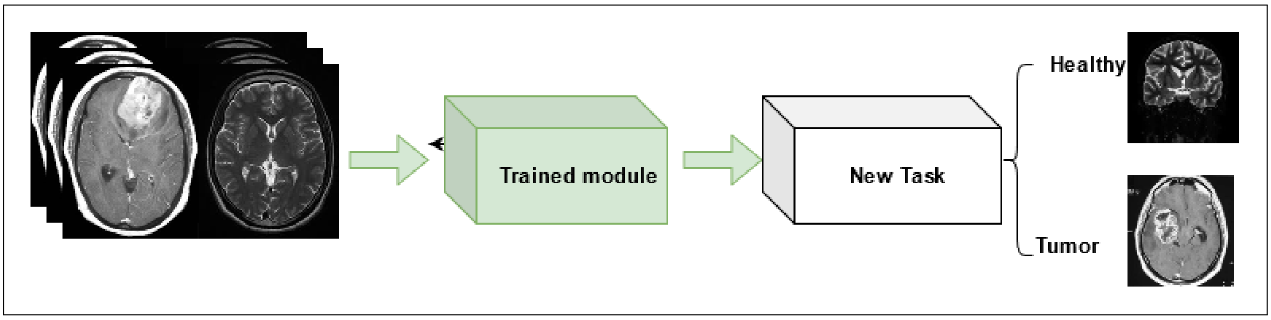

Figure 9: Working of Pre-trained Module

This is referred to as Feature Extraction. The feature maps should contain the essential information from the source data, allowing the intended job to be completed using this deductive method rather than the original data in its entirety. Several machine learning modules are effective for tumor identification, as indicated in the literature study, although AlexNet is the most accurate. By activating the Convolutional and Max

Pooling Layers and suspending the Entirely Connected Layers (Dense Layers), AlexNet was used to provide features from MRI scans in this research. The Convolutional and Max Pooling Layers extracted greater-level and lower-level behaviour, respectively.

4 Design Specification

The workflow of entire research is shown in Figure 10. Three transfer learning modules are applied in this research which are CNN, AlexNet, SVM+HOG. The pretrial models play a vital role in analysis for feature extraction. Feature extraction reflects on the most crucial data that an image may give for a complete description of a lesion. It is a method which is used to obtain the most influential features that are symbolic of the many kinds of objects and photographs. Features are used as inputs by classifiers to assign the class. Feature extraction aims to minimize the original data by identifying and quantifying the qualities, that distinguish one input sequence from another. The extracted feature should deliver the input by transforming the specification of the images associated attributes into feature vectors. As a novel approach it takes less time for brain tumor detection process and gives significant accuracy.

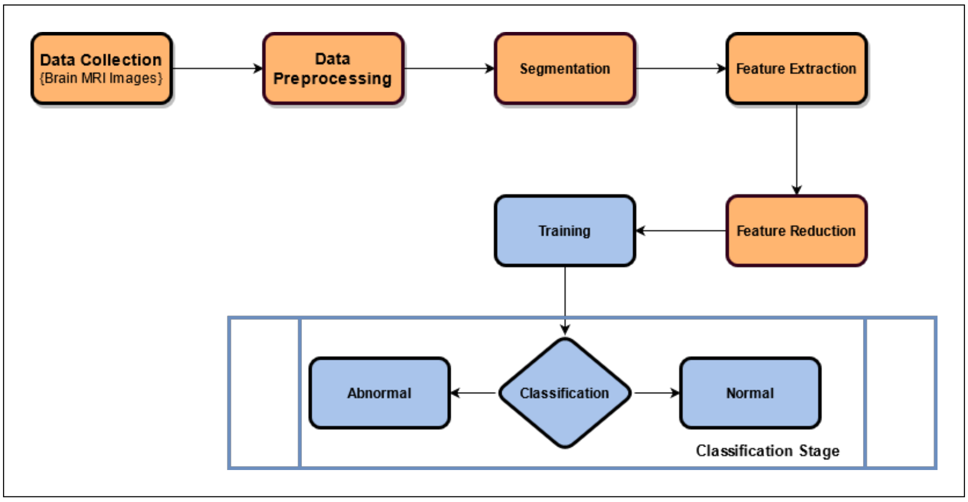

Figure 10: Flowchart of research design

5 Implementation

This section explains how the Transfer Learning models are used to accurately identify brain tumor based on Magnetic Resonance Images (MRI).

5.1 Setup

CNN and other models consume long time to process the visuals. The experiment is conducted on a Google Collaboratory environment with a 100 GB hard drive, 12.72 GB RAM, and a 48.97 GB run-time GPU. Because all models have additional layers, they take longer to execute on big picture data. The use of a GPU in real time speeds up the execution of CNN and AlexNet. The python libraries Keras and TensorFlow are utilized to implement all three models. On Google Collaboratory Notebook, Python version 3 is used. Google Drive has been used to store the data. Numpy and Keras packages from Python are used for image normalization, argumentation, cropping and up-sampling.

5.2 Data Handling

Initially, dataset is loaded from Google Drive, the dataset contains two folders, Yes or No. 'Yes' folder contains real brain tumor images and 'No' folder contains healthy clots or brain images of patients that don't have tumor. The API and data source are trustworthy, and the collected data has the best quality. Initially the required cleaning, transformations, and data processing activities have been completed in Python. Image Augmentation, libraries of Keras and Tenserflow are used to determine the same size for all the data, which allowing the model to be more generalized and accurate. After that in the pre-processing stage augmentation and transformation performed on dataset then the processed data sorted into training and testing sets. The obtained data has been split into two parts, 70% of the data is passed to the training set, and remaining 30% is assigned to the testing set. All three transfer learning algorithms have provided the training data one by one. A tumor may be incorrectly detected by analyzing tiny parts of photos or clusters. Geometric restrictions are applied to a cluster to eliminate clusters with segmentation threshold values that are less than the required threshold benefit value. This research must deal with the influence of main characteristics on throughput in post-processing, all of which help in the extraction of function patches. At the end, the components are taken out for additional analysis and all the parameters are tracked for the unusual procedure. Strategies that use the same database depend on Transfer Learning for feature extraction.

5.3 Transfer Learning

Transfer learning applies the characteristics already known to tackle one problem as a starting point to tackle other problems by utilizing the pre-trained model for developing basic distinct data. Pre-trained models that were trained using MRI scans were used in this investigation. These networks use the entire input image and then offer probability outputs of its labels for each element in the image.

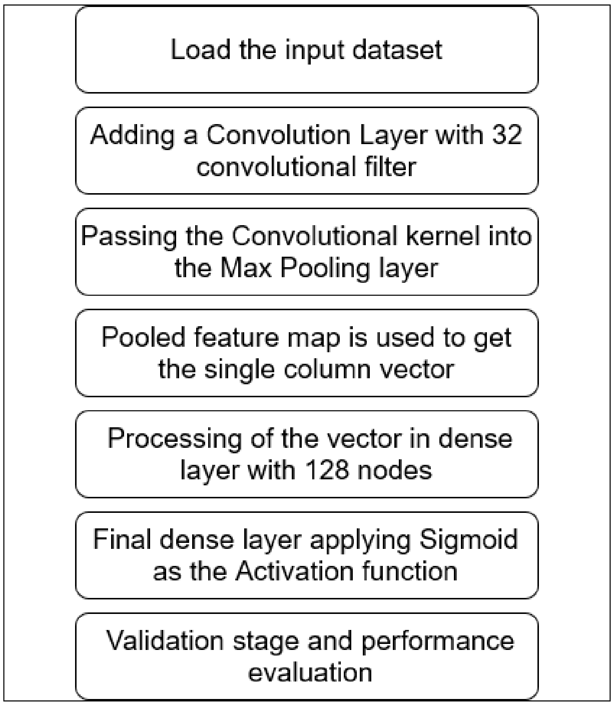

Figure 11: Workflow of AlexNet

6 Evaluation

This section focuses on the study of three models as well as all the factors that have been fine-tuned to get the best three models applied for this research investigation MRI image dataset on the Kaggle. AlexNet and HOG are used as novelty in this research for Brain Tumor Detection. The losses and accuracy of the process are computed for each epoch for models during the assessment phase. Accuracy and loss plots are displayed. The test accuracy is computed as a ratio of prediction and test data. Every model's confusion metrics are computed to get a genuine positive and true negative result.

6.1 Initial Experiment : CNN

All MRI images are sent into the CNN model as training and testing data. The Convolutional neural network was already pre-trained for MRI Dataset. As shown in Figure 12 CNN training accuracy was 0.96 and the test accuracy was 0.88. We can observe increasing epochs lids to increasing Accuracy and decreasing loss. Also we get fluctuating accuracies with various size of images. Finally, we get maximum accuracy for CNN model i.e. 0.88 at the 240*240 image size

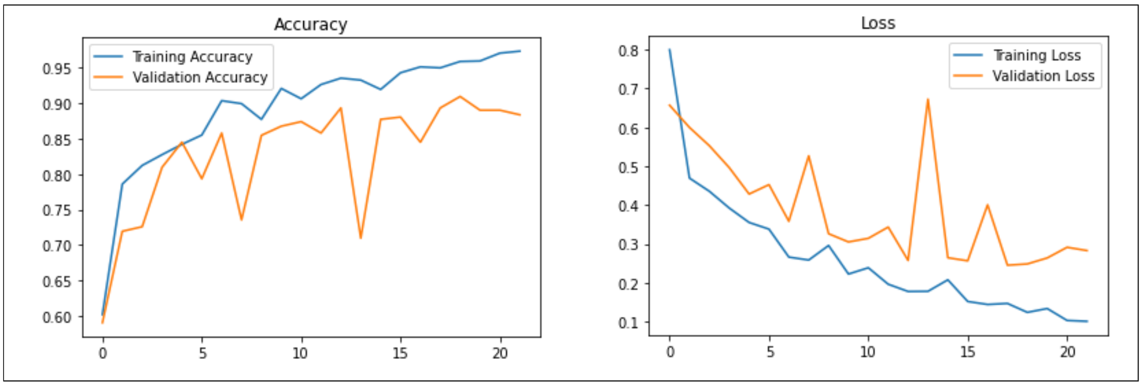

Figure 12: Graphs for CNN output

6.2 Novel Experiment 1 : AlexNet

In this experiment, a pre-trained AlexNet convolutional neural network model has been used that was fine-tuned by freezing portions of the levels to minimize overfitting. AlexNet is a fully connected Convolutional layer CNN model. The size of the MRI image input is 240x240. Across the network, it comprises of Convolution layers with a fixed 3x3 feature map and 5 Max pooling layers of 2x2 size. The two fully linked layers are placed at the top with a softmax output layer. AlexNet Model is a big network that builds deep neural networks by stacking several convolutional layers to increase the capacity to learn hidden information. All preprocessed data are sent to Pre-train AlexNet model. We can see the maximum test accuracy result for this model as shown in Figure 14.

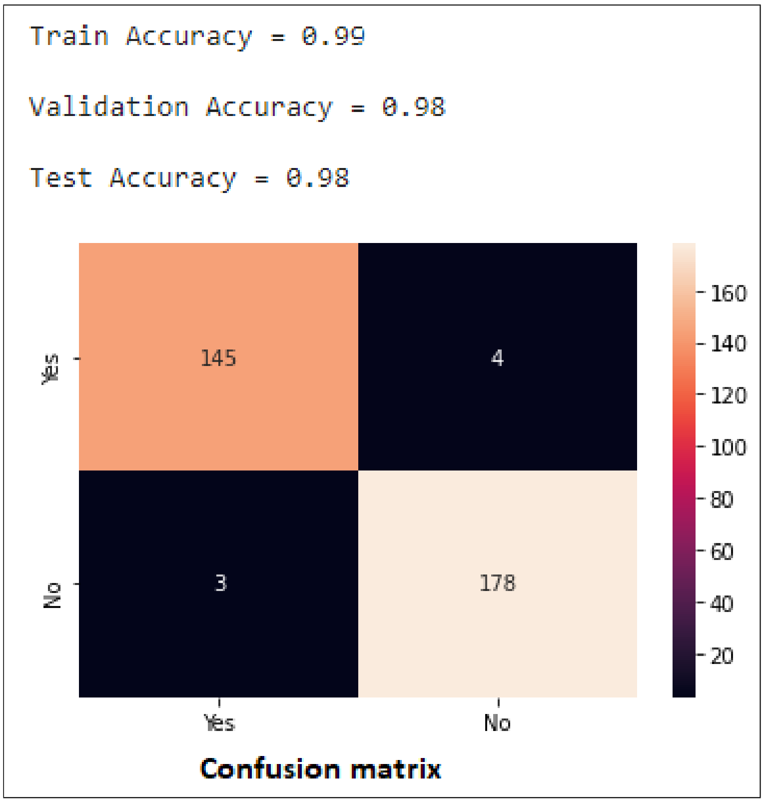

Figure 13: Accuracy and Confusion matrix for Alexnet

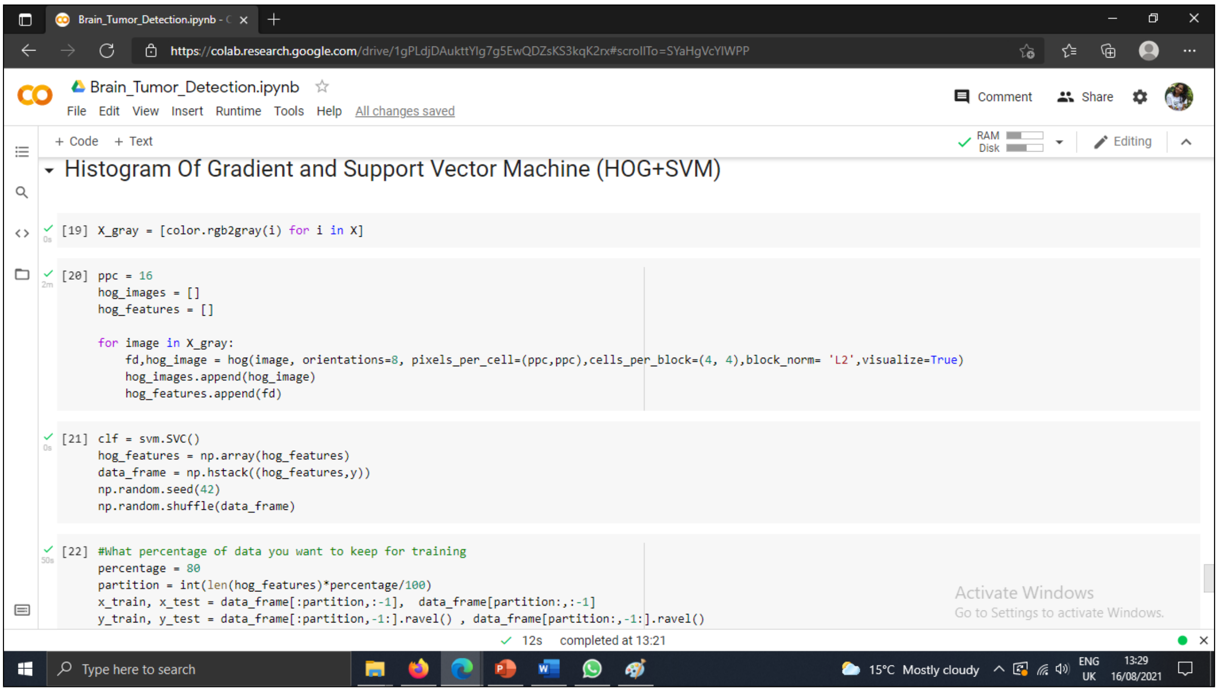

Figure 14: Precision matrix for Alexnet

6.3 Novel Experiment 2 : SVM+HOG

The suggested system produces a fair appropriate result for input MRI Scans. The HOG is used for segmentation, while the SVM is used for feature mapping and matching in the implemented algorithm. There were several approaches to identify brain tumors before this system, such as AlexNet, and only simple CNN was employed for tumor identification. This model gives a accuracy 0.93 Figure 16 as compared to other models.

```
print("Accuracy: "+str(accuracy_score(y_test, y_pred)))
```

```
Accuracy: 0.9322033898305084
```

```
cm = confusion_matrix(y_test, y_pred)
df_cm = pd.DataFrame(cm, index = ["Yes", "No"], columns = ["Yes", "No"])
sn.heatmap(df_cm, annot=True, fmt='g')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9b3b606490>
```

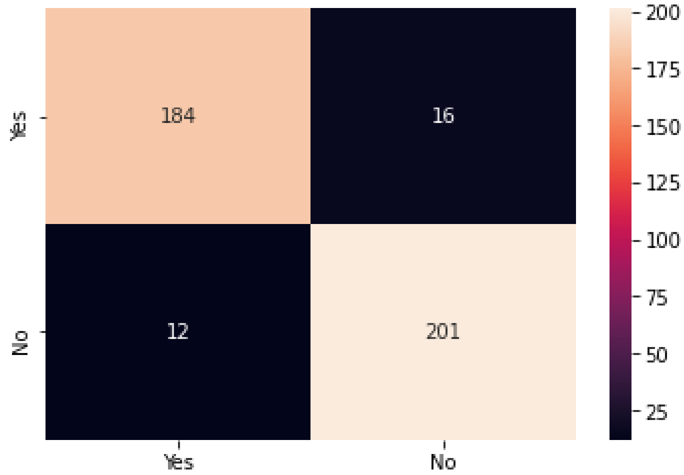

Figure 15: Accuracy and Confusion matrix for SVM+HOG

```
tumor.accuracy_model(model=clf, X=x_test, y=y_test, tp = 'Test', precv=True)

Test Accuracy = 0.91

Precision Matrix
[0.89252336 0.91959799]
```

Figure 16: Precision matrix for SVM+HOG

6.4 Discussion

The achievement of this research is increasing the accuracy and precision value for brain tumor detection. Using Google Colab environment helps to reduce the processing time and gives a significantly accurate result. The average accuracy for all the models is good but specific accuracy and minimal loss is majorly seen in AlexNet which is 98%, following that we got second highest accuracy for SVM+HOG which is 93%. Different accuracy values were obtained for various sizes of images. This was then applied to the pre-train model for images of size 240x240, giving a maximum accuracy result. The combination of CNN, AlexNet, and SVM+HOG is better as compared to other models. As seen in Figure 17 more than two models and AlexNet were used, giving higher accuracy in minimal time as compared to other models. This model can be used for detection of brain tumor in medical field which will give results as early as possible.

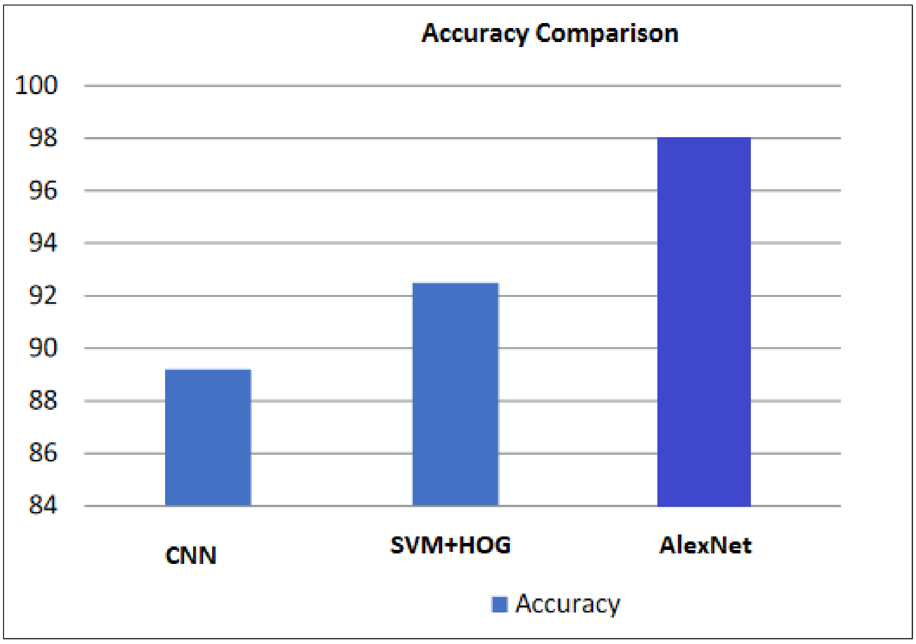

Figure 17: Comparison of implemented models

7 Conclusion and Future Work

Three transfer learning models were used in this study to detect brain tumors utilizing magnificent resonance images (MRI). The proposed approach improves accuracy to 98% as well as reduced execution time. The research combines multiple technologies, such as the CNN model, model used for a quick and accurate finding of the tumor on MRI image data, and the Alex Net efficient classification method, which is utilized to effectively categorize the identified tumor location. For item labelling, HOG and SVM was used, as well as the wavelet transform for pre-processing and skull masking. As a result, the effect of this entire combination is significant than separate modules or any other combinations.In comparison to previous transfer learning approaches, the model's accuracy is remarkable and dependable. The suggested method's merit is that the model learns about the instances quickly, resulting in excellent accuracy at initial epochs.

In future, we can apply this module to detect other cancers such as Lungs cancer, Breast cancer. Also we can use R-mask to improve more accuracy.

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