# ABSTRACT

The majority of primary central nervous system (CNS) tumours are brain tumours, which account for 85 percent to 90 percent of all cases. Cancer of the brain and nervous system is the tenth leading cause of death in both men and women. As such accurate and early detection of such tumours are extremely necessary to pave way for treatment.

Isolation of abnormal tissues from normal brain tissues is one of the most important tasks of any brain tumour detection system. Interestingly, the field of brain tumour analysis has successfully applied medical image processing principles, especially on MR images, to automate the core steps of tumour proximate detection, such as extraction, segmentation, and classification. The non-invasive imaging properties of MR have prompted further research. Given the diversity of shapes, areas, and sizes of tumours, computer-aided diagnosis or detection systems are becoming more elusive and remain an open problem.

In this project we focus on the aspect of improving the brain tumour detection system by improving pooling layer functionality with the concept of wavelet pooling. We replace **traditional max pooling** with **wavelet pooling** to improve accuracy.

# CONTENTS

# 1. INTRODUCTION

## 1.1 Definition of Computer Aided Diagnosis(CAD)

Computer-aided detection (CADe) or computer aided diagnosis (CADx) is a computer based tool that assists doctors in making quick decisions in the field of medical imaging.Medical imaging is concerned with image details that medical practitioners and doctors must interpret and examine abnormalities in a limited time period.Image analysis is a critical role in the medical field because imaging is a simple modality for quickly diagnosing diseases, but image acquisition must not affect the human body. Imaging techniques such as MRI, X-ray, endoscopy, ultrasound, and others produce high-quality images but damage the human body; as a result, images are obtained with less energy, resulting in poor image quality and low contrast.CAD systems are used to enhance image quality, which aids in accurately interpreting medical images and processing them for highlighting the identifiable portions. CAD is a technology that combines concepts such as artificial intelligence (AI), computer vision, and medical image processing. The primary use of a CAD device is to detect abnormalities in the human body. Detection of tumours is the most common application, and if it is missed during basic screening, it can lead to cancer.

The primary aim of CAD systems is to detect abnormal patterns that a human professional might miss. For example, Identification of small lumps in dense tissue, architectural distortion, and prediction of mass form as benign or malignant based on shape, scale, and other factors in mammography,etc.

## 1.2 Significance and applications of CAD

CADe is typically limited to identifying the identifiable parts or structures in an image, while CADx aids in the evaluation of the structures defined in CADe. The CAD models, when used together, are more effective at detecting abnormalities at an early stage. The system aids the radiologist in reaching a decision. Een though CAD has been in use for over 40 years, it nevertheless fails to produce the desired results. CAD cannot replace a doctor, but it does help radiologists make informed decisions.In medical diagnosis, it serves as a supporting and final interpretive factor.

CAD is used to diagnose breast cancer, lung cancer, colon cancer, prostate cancer, bone metastases, coronary artery disease, congenital heart defect, pathological brain detection,Alzheimer's disease, and diabetic retinopathy, as well as coronary artery disease, congenital heart defect, pathological brain detection, Alzheimer's disease, and diabetic retinopathy.

### 1.3 Computer Aided Diagnosis System for brain Tumour Detection

The most appropriate method of treatment for brain cancer is determined by accurately detecting the tumor's type, location, scale, and borders. Physicians use computer-aided diagnosis (CAD) systems to help them address the problem. We plan to design and build such a system whilst addressing the challenges of low accuracy and specificity.We look at the various ways to enhance the performance and propose the concept of using wavelet pooling replacing traditionally used max pooling and thereby comparing the result achieved in both cases.

## 2. SURVEY OF EXISTING SOLUTIONS USING WAVELET

**Sarhan M. Ahmad (2020)** proposes a novel computer-aided diagnosis (CAD) technique for the classification of brain tumours in MRI images. The proposed device extracts features from brain MRI images by taking advantage of the Discrete Wavelet transform's strong energy compactness property (DWT). The Wavelet features are then used to characterise the input MRI image using a CNN. The proposed system's cascade functions begin with a wavelet decomposition of the input image I, which is an MRI image that represents any possible image in the used brain tumour dataset.T1-weighted contrast enhanced images from 233 patients with three types of brain disorders were used in this brain tumour dataset.The Wavelet Transform (Wavelet decomposition),is a lossless decomposition function.At the first step of decomposition, the input image yields two vectors of coefficients: approximation and detail coefficients.

The approximation coefficients generate two sets of approximation and detail coefficients, each half the length of the original approximation vector, in the second level of decomposition. For each subsequent step of decomposition, the approximation coefficients are further divided into two new vectors by the decomposition procedure.

Finally, for classification, the function vector (approximation coefficients) is presented to a CNN and an SVM. The SVM and the proposed WCNN system are both trained using the same sets of inputs and outputs

Approximately 70% of the data was used for training and 30% was used for testing. The proposed system tries to categorise an input picture into one of three categories (meningioma,glioma,and and pituitary tumor). For the first experiment, the proposed WCNN method has a maximum success rate (accuracy) of 98.5 percent.For the next experiments effects of using different wavelets were observed.To conclude, by using a decomposition stage of two and the Haar wavelet, experimental tests on the Figshare(Cheng) database achieved 98.5 percent recognition accuracy.And thus according to simulation performance, the proposed method consistently outperforms the SVM system in terms of success rates was established.

**Rossetto M Allison et al Zhou Wenjin (2019)** asserted Wavelet pooling methods may help Convolutional Neural Networks improve their classification accuracy . While combining wavelet pooling with the Nesterov-accelerated Adam (NAdam) gradient calculation process the accuracy percentage of CNN was improved. They used both a Haar wavelet (WavPool-NH ) and a Shannon wavelet to implement wavelet pooling with NAdam (WavPool-NS).

On the LIDC-IDRI data-set, the WavPool-NH and WavPool-NS implementations achieved an accuracy of 95.92 percent and 95.52 percent, respectively. This was an improvement over the 92.93 percent accuracy obtained with the max pooling approach on this data collection.

Wavepooling approaches also prevent overfitting, which is a problem with max pooling.WavePooling also performed well on the CIFAR10 data collection, but overfitting was a problem with all of the methods used.In particular, it was asserted that wavelet pooling has the potential to outperform current methods when combined with an adaptive gradient and wavelets selected specifically for the data.

In conclusion it was noted that improving pooling methods alone isn't enough to change most applications significantly. To build better CNN pipelines, Wavepooling and related approaches must be used in combination with other techniques.

## 3. Objective

Our aim is to use wavelet pooling to boost the classification accuracy of a computer-aided diagnosis method. In this project,we work on replacing traditional maxpooling with wavelet pooling. The main objective of this study is to show that when working on brain tumour diagnosis,wavelets can be used as a reliable and better pooling tool.

## 4. Problem Statement

The problem revolves around the fact that even with years of usage of CAD for disease detection there still are challenges to achieve :

- Accuracy
- Sensitivity
- Specificity

Our challenge is to build and train a highly accurate computer aided diagnosis system for brain tumour so as to cater to the existing problems.

We aim to develop an easily accessible helping tool for early detection of the disease with accurate results.

# 5. ALTERNATE SOLUTIONS

## A. Improving dataset

### i)Increasing data samples

The training of deep learning models typically requires a large amount of data. In general, the more data there is, the better the model will perform. The issue with a lack of data is that our deep learning model may not be able to learn enough patterns or features from the data, and therefore may not perform well on unlabeled data.Hence increasing the number of data samples will directly affect the performance of any system being developed.
The challenge of less data being available to us is very common in the case of deep learning models hence the need of data augmentation arises.

### ii)Data Augmentation

How to get more 'data' when we don't have any? We just need to make small changes to our current dataset to get more information. Flips, translations, and rotations are examples of minor changes. In either case, our neural network will recognise these as distinct images. Invariance is a property of a convolutional neural network that allows it to reliably identify objects even when they are positioned in different orientations. A CNN, in particular, may be insensitive to translation, perspective, scale, or illumination.

This is basically how data augmentation works. In the real world, we might have a dataset of images captured under a specific set of circumstances. Our target application, on the other hand, can exist in a number of configurations, including various orientations, locations, scales, and brightness levels. We account for these scenarios by using synthetically altered data to train our neural network.

## B. Improving Model Performance

### i) Convolutional Layer : Deeper Network Topology

A wide neural network can be trained with any possible input value. As a result, these networks excel a memorization but struggle with generalisation. However, there are a few drawbacks to using a very large, shallow network. While a large neural network will consider every possible input value, we won't have every possible value for training in the training set.

Deeper networks capture the inherent "hierarchy" that can be seen all over the world. Multiple layers have the advantage of being able to learn features at different levels of abstraction. Therefore deeper networks are preferred over wide shallow network.

To achieve good results, we want our network to be as limited as possible.It will take longer to train the wider network.Deep networks on the other hand need a lot of computing power to train.Hence it's advisable to make them wide and deep enough to work, but no wider or deeper.

### ii) Improving pooling layer functionality:wavelet pooling

Since convolutional neural networks deal with the full picture, the number of neurons and thus the computational cost grows. As a result, we'll need some kind of control over the size of our data and parameters. Pooling methods range from simple deterministic methods like max pooling to more complex probabilistic methods like stochastic pooling. All of these approaches use a neighbourhood approach, which introduces edge halos, blurring, and aliasing while still being fast. Max pooling is an easy strategy that normally works, but it's a little too simple and overfits.Average pooling,is even more prone to overfitting and it might result in blurriness in some datasets.We thus propose the usage of wavelet pooling which might be a safer choice against the rest.

Our main focus in this project is to replace the traditional max pooling with wavelet pooling and to show how it contributes to achieve higher accuracy.We explore how the choice of wavelet basis affects the performance of the network.

We will now move into various technologies and terminology used in our project:

# 6. Deep Learning

Deep Learning is a sub-field of Artificial Intelligence that uses artificial neural networks to learn features from the input data. The word 'deep' signifies the many hidden layers used in the neural network architecture.

## 5.1 TRANSFER LEARNING

- Transfer learning is when we adapt what we learned while solving one problem to a different but related problem. For instance, knowledge gained while learning to recognize cars can be applied to recognize trucks to some extent.
- Transfer learning is a widely adopted practice as training a deep learning model is very much computationally expensive and often the parameters learned can be used across different problem statements

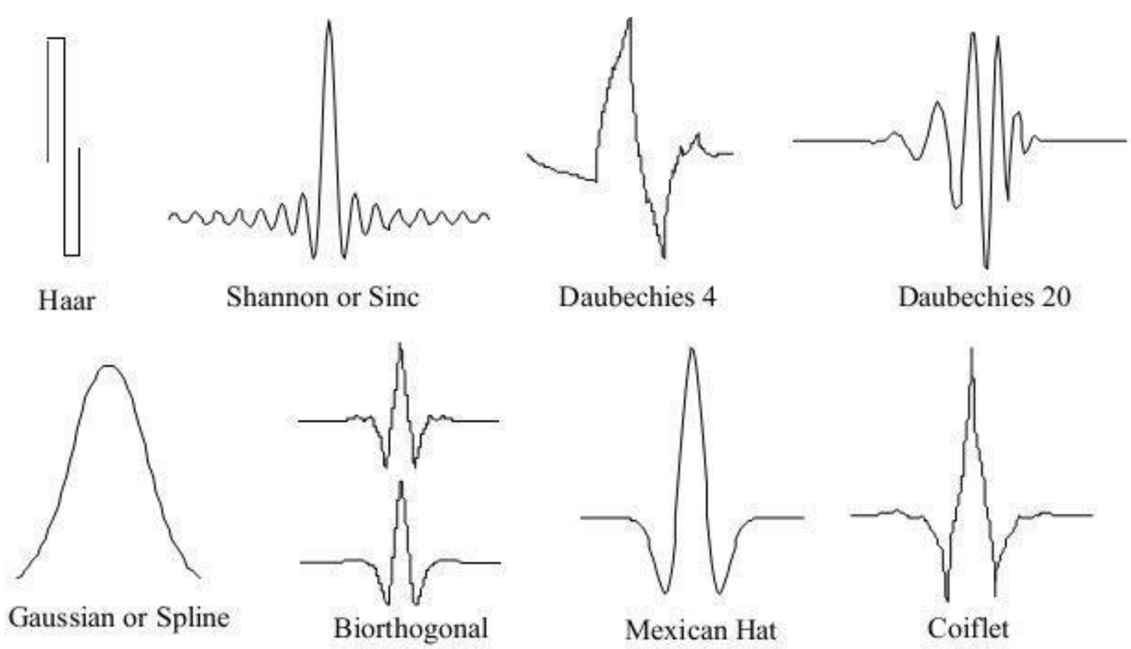
Transfer learning is a machine learning technique in which a model created for one job is utilised as the basis for a model on a different task.

Given the vast compute and time resources required to develop neural network models on these problems, as well as the huge jumps in skill that they provide on related problems, it is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks.

## 7. WAVELET

Signals generated or captured in the real world exhibit slowly changing trends or oscillations punctuated with transients. These abrupt changes in between smooth regions are often the most important part for analysing and gathering information. Edge detection and analysis is an application of this principle in the domain of image processing. Various transforms exist for analysing such waves and signals. Each of these transforms has its usage , advantages and disadvantages. In this report we discuss one such transform, the wavelet transform.

Wavelets are rapidly decaying waves like oscillation that have 0 mean and 0 area under the curve. Some of the popular types of wavelets used are shown in the fig below



In our approach we use the Haar wavelet function defined as Ψ(t), and a scaling function,ϕ(t).These are defined as follows:

$$\Psi(t) = \begin{cases} 1 & 0 \leq t \leq \frac{1}{2} \\ -1 & \frac{1}{2} \leq t \leq 1 \\ 0 & otherwise \end{cases}$$

$$\phi(t) = \begin{cases} 1 & 0 \leq t \leq 1 \\ 0 & otherwise \end{cases}$$

Let us outline some of the fundamental operations in wavelet. We assume wavelets are defined by the **wavelet function** ψ(t).

1. Scaling: Scaling is the process of stretching or shrinking the signal in the time t. It is expressed as :

   $\Psi(\frac{t}{s})$, where s is the scaling factor

   Scaling or stretching a wave helps in capturing slowly varying changes in a signal . A compressed wavelet helps in capturing the abrupt changes.

2. Shifting: Shifting is the delaying or advancing the onset of the wavelet along the length of the signal. It is expressed as Ψ(t-k), where k is the center of the shifting operation. Shifting is done to align with the feature that we are looking for in a signal.

Wavelet transform can be Continuous (Continuous Wavelet transform) in nature or discrete (Discrete wavelet transform in nature). Whereas CWT is more used in time frequency analysis and filtering of time localised frequency components, we focus more on the DWT for our image analysis task.

We can represent a discrete function f(n)as a weighted summation of wavelets $\Psi(n)$,plus a coarse approximation $\phi(n)$

Where j is an arbitrary starting scale , and n = 0,1,2, ..... M

$$W_{\Phi}(j_0,k)=\frac{1}{\sqrt{M}}\sum_{x} f(x)\,\varphi_{j_0,k}(x)$$

Approximation coefficients

$$W_{\Phi}(j_0,k)=\frac{1}{\sqrt{M}}\sum_{x} f(x)\,\varphi_{j_0,k}(x)$$

Detail Coefficients

$$W_{\Psi}(j,k)=\frac{1}{\sqrt{M}}\sum_{x} f(x)\,\psi_{j,k}(x)$$

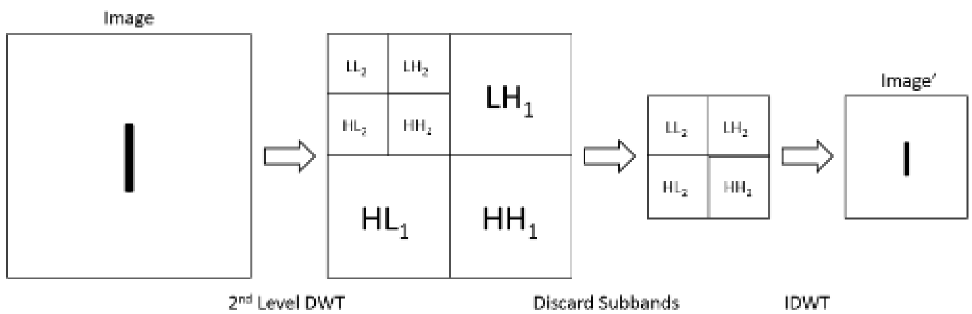
DWT is ideal for **noise robustness** and compressing signals and images as it helps to represent many naturally occurring signals and images with fewer coefficients which enables a sparse representation.

**Wavelet pooling**

In wavelet pooling , wavelets are used as a tool to downsample the feature map dimensions. The major advantage of wavelet pooling over other commonly used pooling techniques like MaxPooling , AvgPooling is that it doesn't use a neighbourhood function to subsample the feature space. This results in fewer unwanted artifacts like jagged lines or increased noise which can reduce the learning capability of a model.

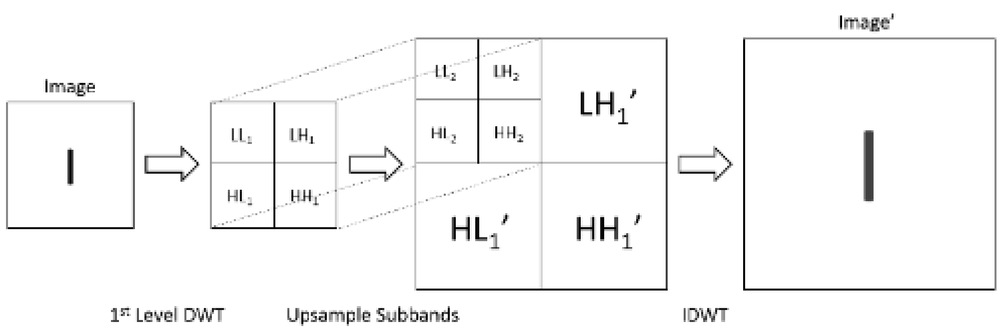
In **forward propagation** , we apply our DWT function twice, once on the rows and then again on the columns. This produces 4 subbands, viz 3 detail subbands (LH,HL,HH) and 1 approximation subband (LL) .

Fig: Wavelet Pooling Forward Propagation phase




In **Backpropagation,** the reverse procedure is applied on the transformed image to get back the original image.

Fig: Wavelet Pooling Backpropagation phase



## 8. TECHNOLOGIES AND ENGINEERING PRINCIPLES USED

**1.Tensorflow:** TensorFlow is an open source machine learning platform that runs from start to finish. It has a large, flexible ecosystem of tools, libraries, and community resources that allow to quickly fabricate and deploy ML applications.

**2.Numpy:** NumPy is a Python library that provides support for huge, multi-dimensional arrays and matrices, as well as a large number of high-level mathematical functions to operate on these arrays.

**3.Matplotlib:** Matplotlib is a visualizing package for Python with NumPy, the Python numerical mathematics extension. It provides an object-oriented API for embedding charts into applications utilising GUI toolkit.

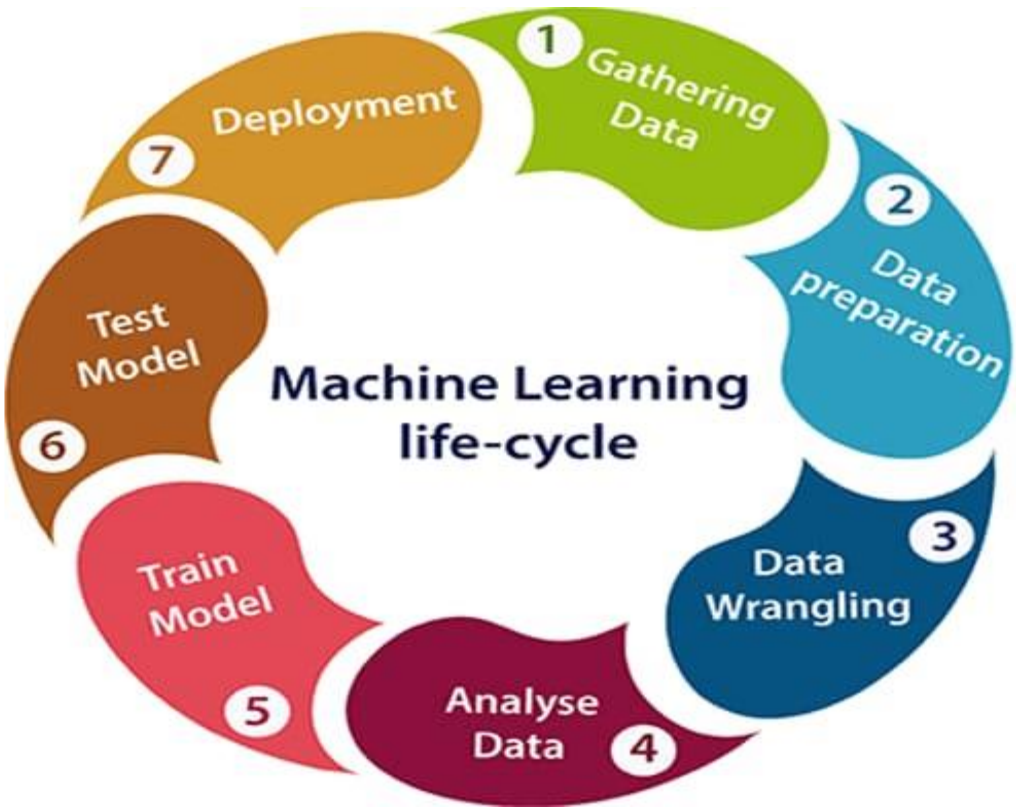
**4.Keras:** Keras is an open-source software library for artificial neural networks that includes a Python interface. Keras serves as a user interface for TensorFlow.

**5.OpenCv:** OpenCV is a package of programming functions focused mostly at real-time computer vision.

**6.PyWavelets:** PyWavelets is a wavelet transform library written in Python. It integrates a high-level interface with C and Cython performance.It is also open-source

**7. FastAPI:** FastApi is a web framework for developing APIs with Python 3.6+ .It is fast and gives high-performance.

**MACHINE LEARNING LIFE CYCLE**




## 1. Data Preprocessing:

Data validation and data imputation are both part of the data-preprocessing process. The purpose of data validation is to determine whether the data is complete and accurate. The purpose of data imputation is to rectify errors and fill in missing values, which can be done manually or automatically by BPA programming.

## 2. Model Building and training:

The development of data sets for training, and production purposes is part of model building. The data analytics experts construct and operate themodel that they built in the previous stage with utmost care. For building and executing the model, they use tools and techniques such as decision trees, regression approaches (logistic regression), and neural networks. This is the stage where we basically train the algorithms to get the desired results. The training parameters are modified by the algorithm during training.It also alters the input data before producing an output.

**3. Model Testing :**

The process of evaluating the performance of a fully trained model on a testing set is referred to as model testing. The testing set, which consists of a collection of testing samples, should be kept distinct from both the training and validation sets, but it should have the same probability distribution as the training set.

**4. Model Deployment :**

Deployment is the process of integrating a machine learning model into a live environment in order to make business decisions.
It's one of the final stages of the machine-learning process.

We implemented our proposed solution in a field where not much work was undertaken neither much progress was made.

The methodology and detailed explantion on our solution is as presented below:

# 9. METHODOLOGY

## 9.1 Dataset

### 9.1.1 Dataset Sample

Dataset Title: Brain MRI Images for Brain Tumor Detection

Link:https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection
For our task we are using a publicly available dataset of brain tumor images which contains a total of 255 MRI images of the brain. The images found in this dataset are collected from google images by the author. These images are classified into 2 categories , one with positive cases for brain tumours and with negative cases.

Division of samples are as following:

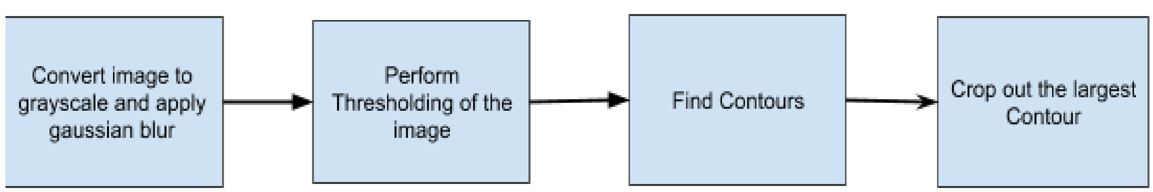
Positive : 155 images
Negative : 98 images

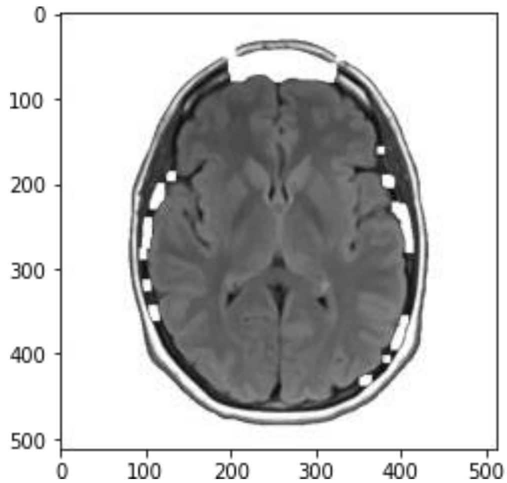
We split the dataset into two parts, viz Training and Testing. Adopting a split ratio of 0.2 , our training set had 205 images from both the class and the testing set had 50 images from both the class.

### 9.1.2 Dataset Preprocessing

Upon inspecting the dataset we find that the images are not of uniform dimensions and also contain other non useful details like scale reference that needs to be removed before working on the data.

To crop out the Region of Interest from each image we used OpenCv to apply thresholding and detect the contours around the skull. The largest contours were grabbed and cropped out to form the final image.





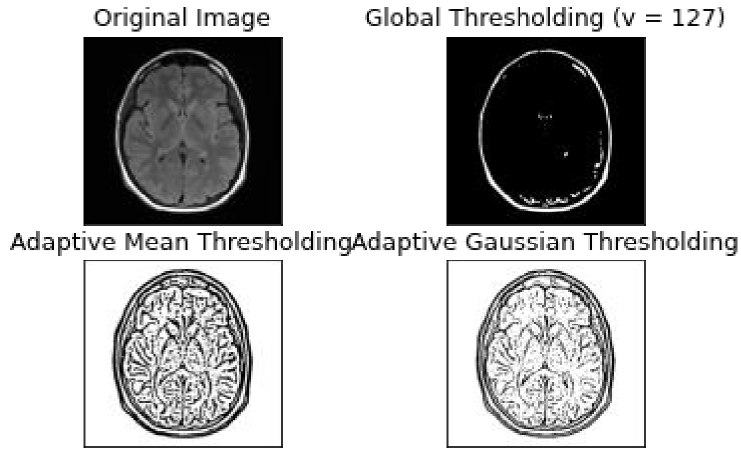
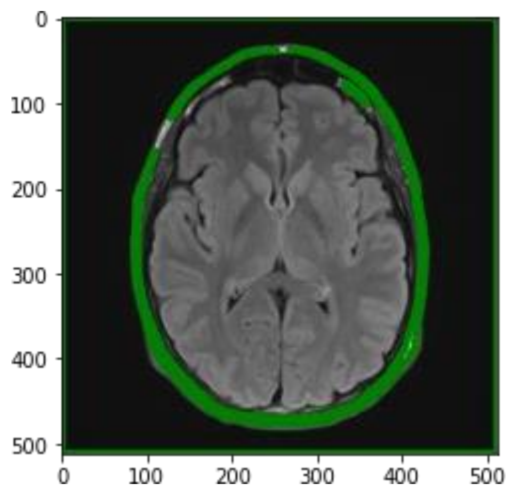




fig :  Original Image
different

fig : Results of
Thresholding techniques



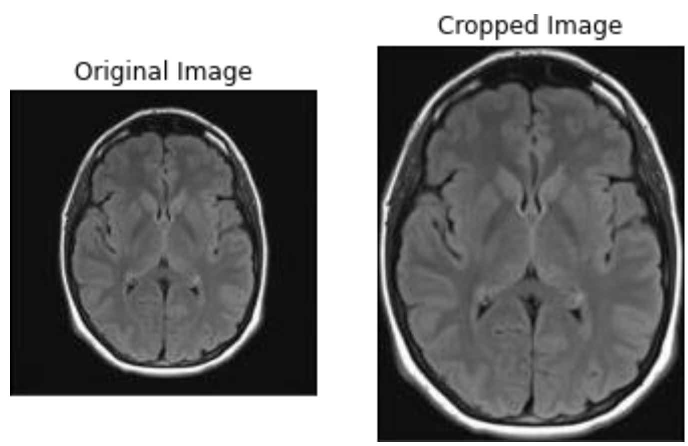




Fig: Detecting the largest contour

Fig: Final Result

### 9.1.3 Data Augmentation

To overcome the limitation of having a small dataset we used data augmentation to transform original images with the help of **Keras ImageDataGenerator.** Data Augmentation is a widely adopted practice in the field of deep learning. As deep learning is highly dependent on available training data, data augmentation is used to increase the data set size. Data Augmentation also acts as a **regularizer** and helps to reduce the **training bias** or overfitting of the model.

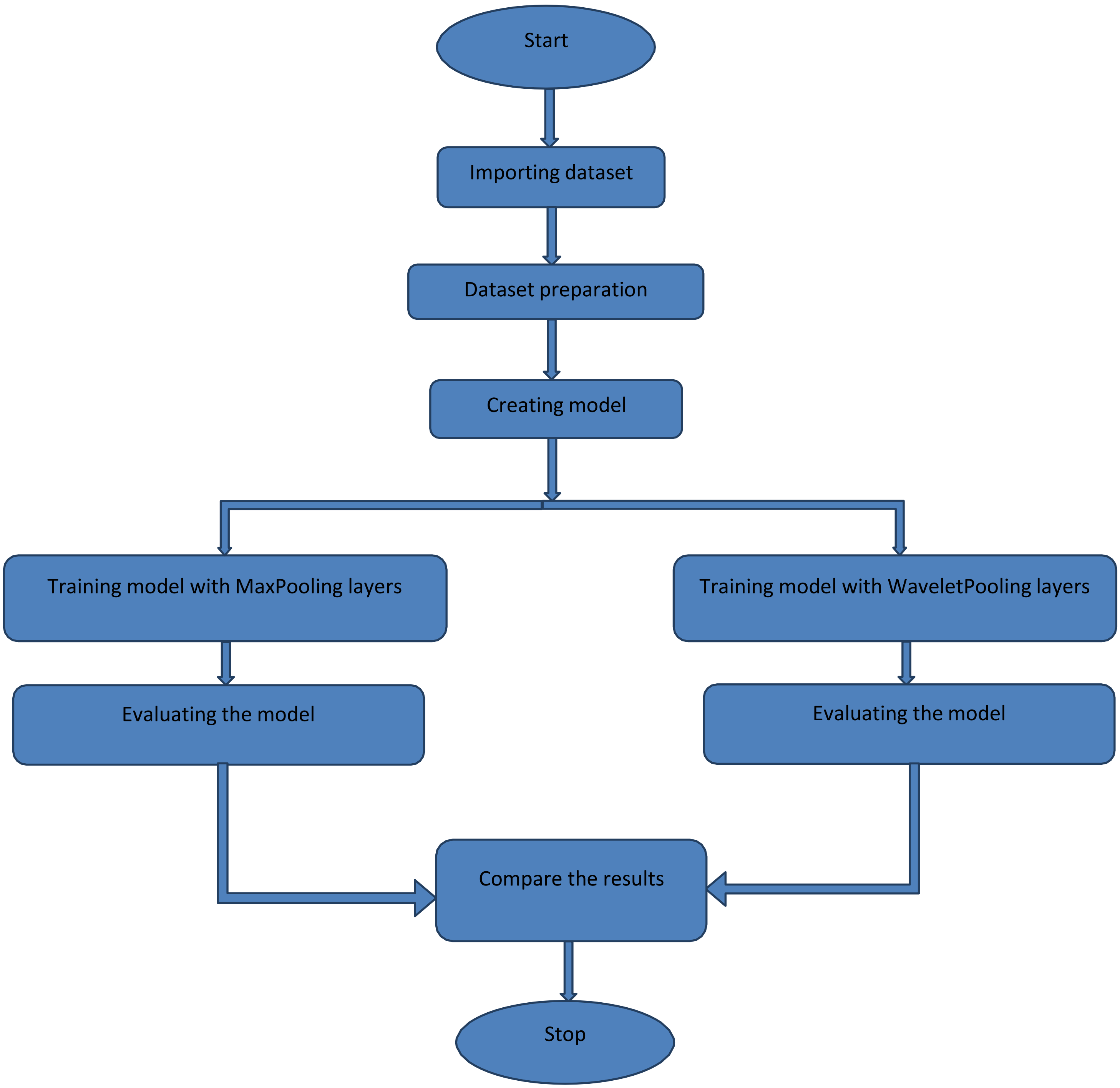
The transformation parameters applied for data augmentation are:

1. Shearing ratio = 0.2
2. Rotation limit = 45 degrees
3. Zoom range = 0.2
4. Horizontal Flip

Data Augmentation using Keras ImageDataGenerator is an ' On the fly' process.The images are not pre transformed and saved to disk but the transformations are only applied at the start of each new training epoch. This ensures all the images are transformed in memory and cleared once the epoch is finished . This approach ensures there's no additional storage cost to store the transformed images as only the original images are stored in the disk at any time

## 9.2 Model Architecture and Methodology

## Flowchart Design

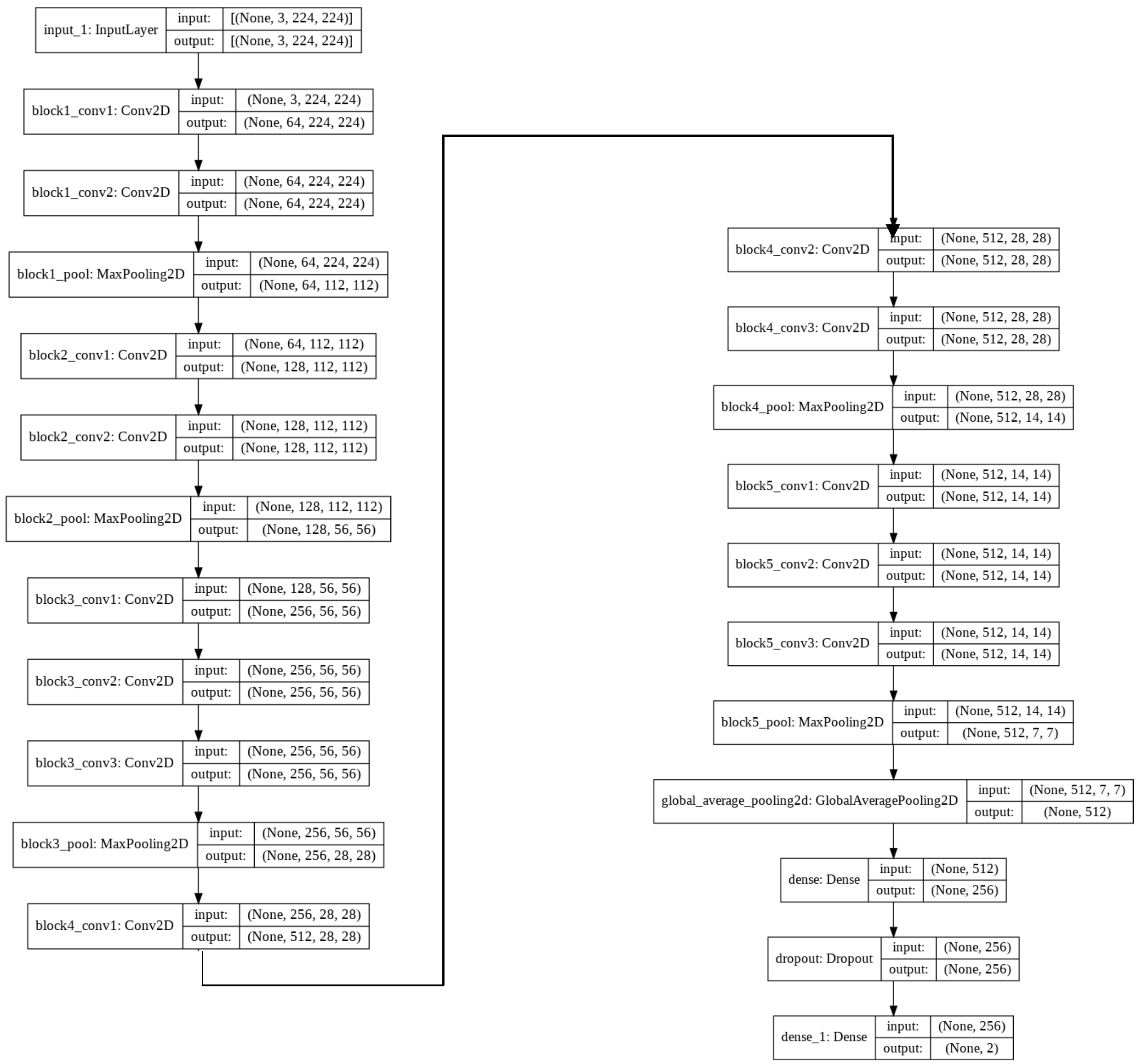


## Approach 1: Using MaxPooling layers

In our project, we use the concept of transfer learning where we preloaded the weights “imagenet” in the model. While training our model, we froze the first 14 layers i.e., the weights of the first 14 layers remain constant and the rest of the layers are trained. We also added few more layers to the base model:

- 1 Dense layer with 256 nodes
- 1 Global Average Pooling layer
- 1 Dropout layer with rate set to 0.2
- And lastly the classification layer

The model summary is as follows:


input_1: InputLayer
input:
[(None, 3, 224, 224)]
output:
[(None, 3, 224, 224)]
block1_conv1: Conv2D
input:
(None, 3, 224, 224)
output:
(None, 64, 224, 224)
block1_conv2: Conv2D
input:
(None, 64, 224, 224)
output:
(None, 64, 224, 224)
block1_pool: MaxPooling2D
input:
(None, 64, 224, 224)
output:
(None, 64, 112, 112)
block2_conv1: Conv2D
input:
(None, 64, 112, 112)
output:
(None, 128, 112, 112)
block2_conv2: Conv2D
input:
(None, 128, 112, 112)
output:
(None, 128, 112, 112)
block2_pool: MaxPooling2D
input:
(None, 128, 112, 112)
output:
(None, 128, 56, 56)
block3_conv1: Conv2D
input:
(None, 128, 56, 56)
output:
(None, 256, 56, 56)
block3_conv2: Conv2D
input:
(None, 256, 56, 56)
output:
(None, 256, 56, 56)
block3_conv3: Conv2D
input:
(None, 256, 56, 56)
output:
(None, 256, 56, 56)
block3_pool: MaxPooling2D
input:
(None, 256, 56, 56)
output:
(None, 256, 28, 28)
block4_conv1: Conv2D
input:
(None, 256, 28, 28)
output:
(None, 512, 28, 28)
block4_conv2: Conv2D
input:
(None, 512, 28, 28)
output:
(None, 512, 28, 28)
block4_conv3: Conv2D
input:
(None, 512, 28, 28)
output:
(None, 512, 28, 28)
block4_pool: MaxPooling2D
input:
(None, 512, 28, 28)
output:
(None, 512, 14, 14)
block5_conv1: Conv2D
input:
(None, 512, 14, 14)
output:
(None, 512, 14, 14)
block5_conv2: Conv2D
input:
(None, 512, 14, 14)
output:
(None, 512, 14, 14)
block5_conv3: Conv2D
input:
(None, 512, 14, 14)
output:
(None, 512, 14, 14)
block5_pool: MaxPooling2D
input:
(None, 512, 14, 14)
output:
(None, 512, 7, 7)
global_average_pooling2d: GlobalAveragePooling2D
input:
(None, 512, 7, 7)
output:
(None, 512)
dense: Dense
input:
(None, 512)
output:
(None, 256)
dropout: Dropout
input:
(None, 256)
output:
(None, 256)
dense_1: Dense
input:
(None, 256)
output:
(None, 2)

Training the model:

For training the model, we use the Adam optimizer with an initial learning rate of 0.01.

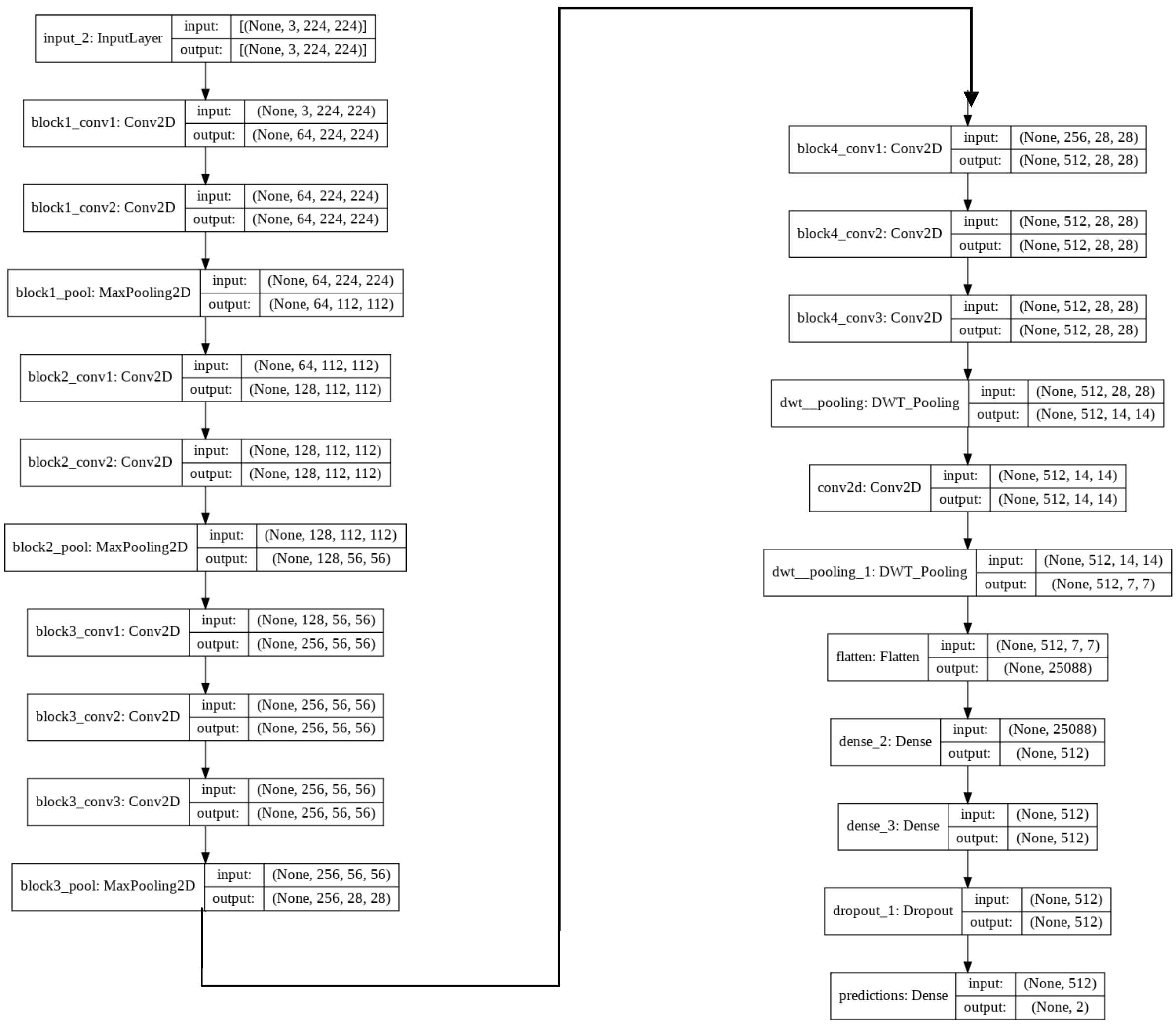
We also set the hyperparameters inside the ReduceLR function like patience=4, factor=0.1 and minimum learning rate=0.0001.

We train the model taking different values of the hyperparameters and the best accuracy obtained was recorded.

**Approach 2: Using WaveletPooling layers**

In order to compare the performance of wavelet pooling with that of max pooling, in our next model architecture we replace the last two Maxpooling layers with DWT_pooling layers and also add an additional convolutional layer.

The model summary is as follows:




Training the model:

We train this newly created model similarly as the previous model and record the best accuracy obtained

**Metrics Used for Evaluation**

Following metrics were used for evaluating the performance of the models:

1. Accuracy : $\frac{\text{TP + TN}}{\text{TP + FP + TN + FP}}$

2. Precision: $\frac{\text{TP}}{\text{TP+FP}}$

3. Recall: $\frac{TP}{TP+FN}$

4. Error Rate: 1 - accuracy

5. Matthews correlation coefficient (MCC):

$$\frac{(\text{TP} * \text{TN}) - (\text{FP} * \text{FN})}{\sqrt{}(\text{TP} + \text{TN}) * (\text{TP} + \text{FN}) * (\text{TN} + \text{FP}) * (\text{TN} + \text{FN})}$$

## 9.3 Results and Discussion

Approach 1 : With traditional Maxpooling approach

On training the traditional VGG network on our dataset for 1000 epoch we get the following metrics:

| Accuracy | Precision | Recall | Error Rate | MCC |
|---|---|---|---|---|
| 92 % | 93.5% | 93.5% | 7.9% | 78% |

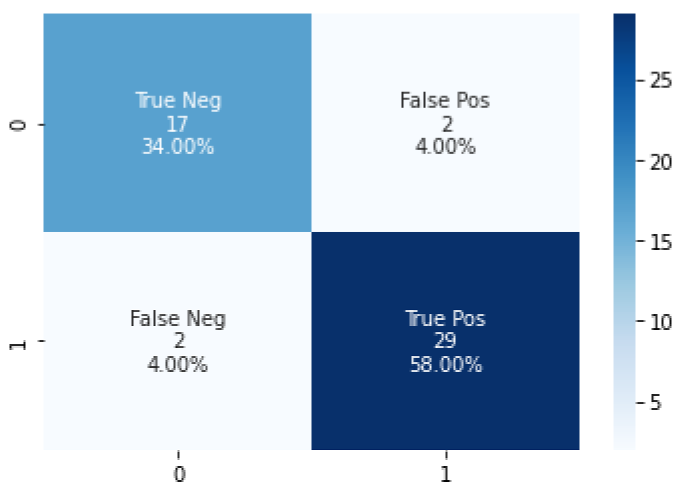
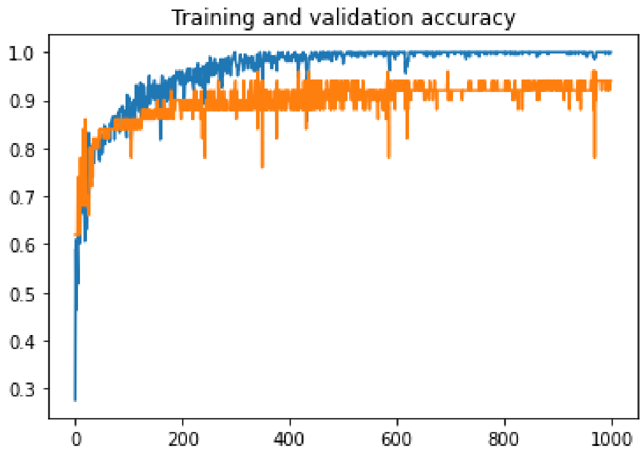
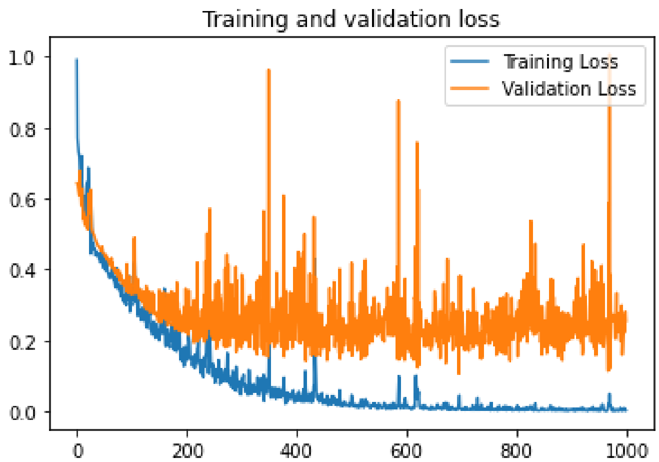



Fig: Confusion Matrix




Approach 2 : With Wavelet Pooling approach

On training the traditional VGG network on our dataset for 1000 epoch we get the following metrics:

| Accuracy | Precision | Recall | Error Rate | MCC |
|---|---|---|---|---|
| 96 % | 96.7% | 96.7% | 4.0% | 91% |

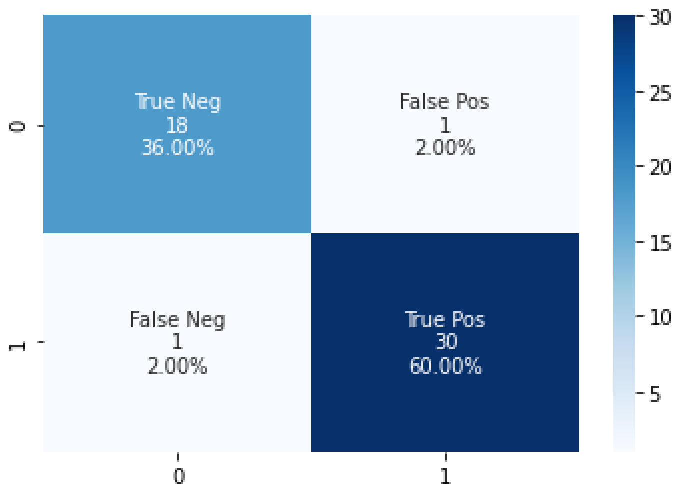
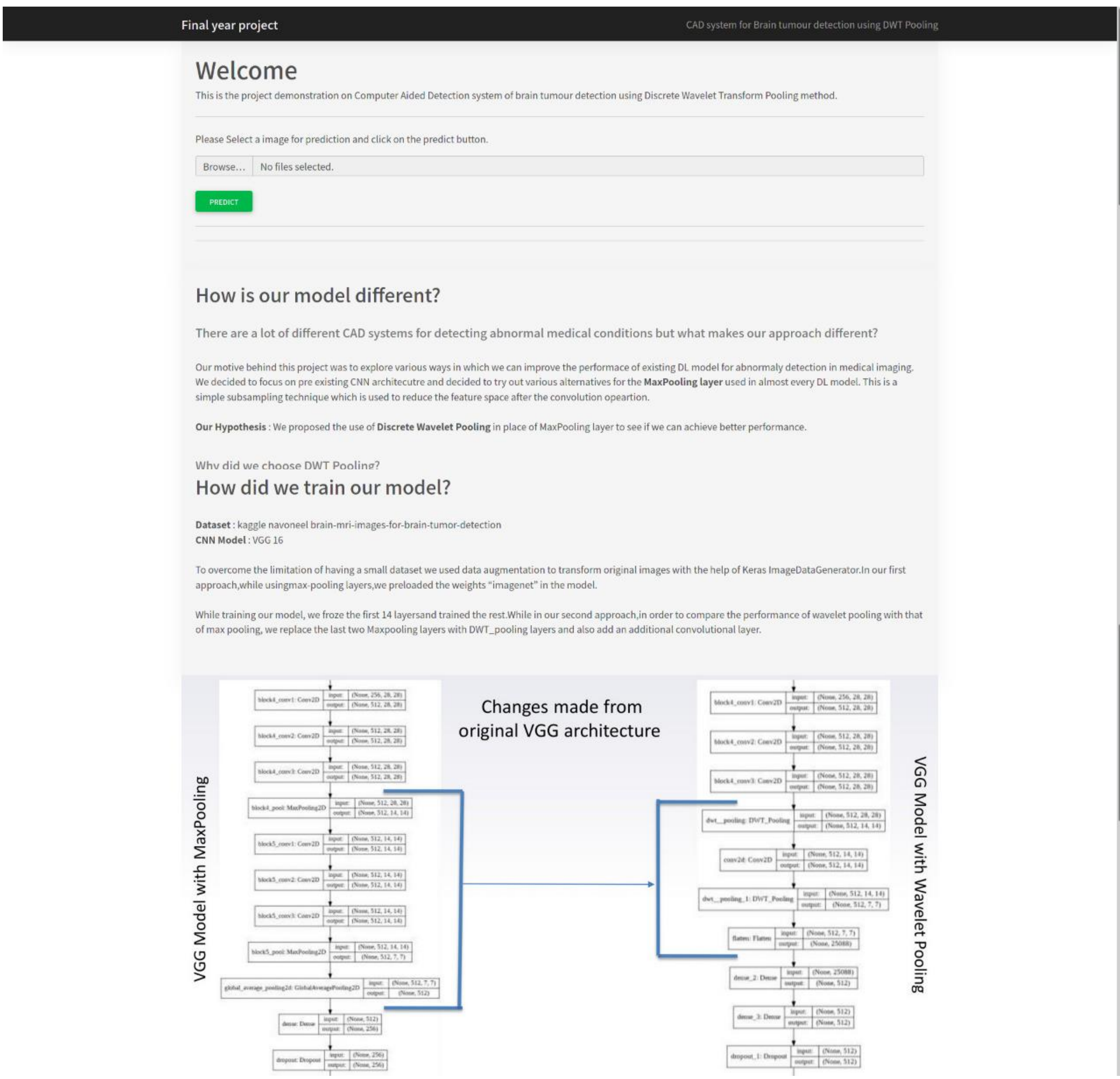



Fig: Confusion Matrix

We notice an improvement in all the metrics with a increase of 4% in accuracy , increase of about 3% in both precision and recall, 3.9% decrease in error rate and 12% increase in Matthews correlation coefficient

## 9.4 Deployment

We finally put together all our findings and built a demonstration website which has the facility to upload images of brain X-ray and predict on them using the CNN models we trained in our earlier stages.We created a simple front end using basic HTML and CSS framework and used FastApi tool to connect the front end with our python logic. FastApi provides simple , fast and asynchronous API gateways which can be called using HTTP request.



## Is our assumption correct?

| Accuracy | Precision | Recall | Error rate | Mcc |
|---|---|---|---|---|
| 92% | 93.5% | 93.5% | 7.9% | 78% |

Results using maxpooling

| Accuracy | Precision | Recall | Error rate | Mcc |
|---|---|---|---|---|
| 96% | 96.7% | 96.7% | 4.0% | 91% |

Results using DWT

We notice an improvement in all the metrics:

- Increase of 4% in accuracy
- Increase of about 3% in both precision and recall
- Decrease 3.9% in error rate
- 12% increase in Matthew's correlation coefficient

Hence we find that our experimental results coincides with our assumption.

Demonstration of CAD brain tumour prediction on a single X ray image.

STUDENTS

Sourav Mazumdar
Hrishikesh Saloi
Debanshi Neog
Shaima Siddiqua

FACULTY

Under the guidance of
Dr Rupam Baruah
HoD CSE
Jorhat Engineering College

Final year project

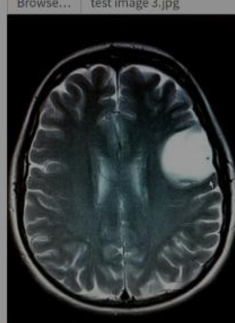
CAD system for Brain tumour detection using DWT Pooling

# Welcome

This is the project demonstration on Computer Aided Detection system of brain tumour detection using Discrete Wavelet Transform Pooling method.

Please Select a image for prediction and click on the predict button.

Browse... test image 3.jpg



PREDICT

**Result:**

Tumour found

OK

## How is our model different?

There are a lot of different CAD systems for detecting abnormal medical conditions but what makes our approach different?

Our motive behind this project was to explore various ways in which we can improve the performace of existing DL model for abnormaly detection in medical imaging. We decided to focus on pre existing CNN architecutre and decided to try out various alternatives for the **MaxPooling layer** used in almost every DL model. This is a simple subsampling technique which is used to reduce the feature space after the convolution opeartion.

## 9.5 Social and Ethical Issues Involved

**An artificially intelligent computer program can now diagnose skin cancer more accurately than a board-certified consultant.Better yet, the program can do it faster and more efficiently, requiring a training data set rather than a decade of expensive and labor-intensive medical education. While it might appear that it is only a matter of time before physicians are rendered obsolete by this type of technology, a closer look at the role this technology can play in the delivery of health care is warranted to appreciate its current strengths, limitations, and ethical complexities**

**This powerful technology creates a novel set of ethical challenges that must be identified and mitigated since AI technology has tremendous capability to threaten patient preference, safety, and privacy. However, current policy and ethical guidelines for AI technology are lagging behind the progress AI has made in the health care field. While some efforts to engage in these ethical conversations have emerged, this powerful technology creates a novel set of ethical challenges that must be identified and mitigated since AI technology has tremendous capability to threaten patient preference, safety, and privacy. One major theme to be addressed in this issue is how to balance the benefits and risks of AI technology. There is benefit to swiftly integrating AI technology into the health care system, however, there is a need to minimize ethical risks of AI implementation—which can include threats to privacy and confidentiality, informed consent, and patient autonomy—and to consider how AI is to be integrated in clinical practice.**

## 9.6 Conclusion

This is the first considerably major and important project undertaken by us during our B.E. course. After completion of the project we have arrived at certain conclusions and we are finally at a position to establish that the purpose and objective of our project is partially achieved.

First we worked on gathering all the information related to CAD and wavelet.We studied about the available models and techniques and chalked out the project outline. We continuously modified and compared the results via trial and error method to achieve the best result as we predicted.We finally deployed the model to be operational in a live environment.
With relatively less research and studies conducted on the wavelet pooling we tried to use best of our knowledge to combine it with different techniques for higher accuracy. The project helped us to practically apply our knowledge of deep learning concepts and also helped us to realize how we can put it to practical use.

Apart from earning the educational benefits from the project for all the team members,the concept of computer aided diagnosis is of utmost importance in real world.It is one of the highly sought development field with a lot of scope for improvement.This project is another work to combat the already existing challenges of this field.

# 10. CHALLENGES AND FUTURE PROSPECTS

We have only worked on a small set of data for our evaluation, future studies would benefit from large dataset with ample amounts of samples which will lead to a more robust and generalised model with less chances of overfitting. To further study the improvement provided by wavelet pooling in Computer Aided Diagnosis, studies can be made on other domains of diseases or diagnosis that can help from a robust classification model like skin cancer, lung disease like pneumonia to name a few.

Further studies can be made using more recent deep learning models like Inception , Xception architectures to see how much gain can be achieved by using wavelet pooling if any.

In this study we have only used the Haar wavelet function, other wavelet functions like Shannon wavelet function, gaussian wavelet function can be used as the basis for the wavelet transform to document what changes are observed when moved to different wavelet functions.

# 11.REFERENCES


- Introduction to Wavelets in Image Processing http://www.leap.ee.iisc.ac.in/sriram/teaching/MLSP_16/refs/W24-Wavelets.pdf
- Accesed: Jan 4th,2021 https://openreview.net/pdf?id=rkhlb8lCZ
- Ahmad M. Sarhan -Detection and Classification of Brain Tumor in MRI Images Using Wavelet Transform and Convolutional Neural Network https://journaljammr.com/index.php/JAMMR/article/view/30539/57249
- Allison M Rossetto and Wenjin Zhou-Improving Classification with CNNs using Wavelet Pooling with Nesterov-Accelerated Adam
- Karen Simonyan∗& Andrew Zisserman, VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION
- https://www.sciencedirect.com/science/article/abs/pii/S0957417420305200
- https://en.wikipedia.org/wiki
- https://journalofethics.ama-assn.org/article/ethical-dimensions-using-artificial-intelligence-health-care/2019-02