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Enhanced Network Classification of Brain Tumors Using the Transfer Learning Model and Aquila Optimization-Based Metaheuristics

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***Abstract*—** Brain tumor classification is a challenging task due to the complexity of tumor characteristics, in tumor shapes, and limitations in image acquisition techniques in CNN. In this study, the Transfer Learning (TL) model is used to improve network classification accuracy and performance when applied to images of brain tumors. Also, to enhance the optimal result in classification, the TL hyperparameters are fine-tuned by the AQ-based Metaheuristics strategy. The results showed that, in terms of accuracy, sensitivity, and specificity, the proposed method performed better than other popular existing methods with a high exactness of 97.14 percent. The proposed method is evaluated and tested in brain tumor MRI dataset image.

Brain tumor classification is a challenging task due to the complexity of tumor characteristics, tumor shape variability, and limitations in imaging technology. This study used the Transfer Learning (TL) model to improve network classification accuracy and performance using brain tumor imaging. In addition, in order to enhance the optimal classification result, the TL hyperparameters are regulated by the Metaheuristics strategy based on the optimization of the Aquila. The results showed that the proposed method was more accurate, sensitive, and specific than the existing popular methods, with a high accuracy of 97.14 percent. The proposed method is evaluated and tested on the images of brain tumor MRI datasets.

***Index Terms*—** **Aquila Optimizer (AO), Convolutional Neural Networks (CNN), Transfer Learning (TL),**

I. INTRODUCTION

In this paper, the novel work is proposed to perform a classification which is the second proposed work of this thesis. In this suggested study, the Transfer Learning (TL) model is used to improve network classification accuracy and performance when applied to images of brain tumors. Also, to enhance the optimal result in classification, the TL hyperparameters are fine-tuned by the Aquila Optimization- based Metaheuristics strategy. Therefore, the performance of the AO-based TL classification is better than the traditional DL models. This chapter is contributed as follows: i) the TL basics and its working are presented, ii) the hyperparameters of TL method are explained, iii) the TL model is presented for brain tumor MRI image classification. This section carries out a discussion of four popular DL methods namely DenseNet121, MobileNetV2, ResNet18V2, and AlexNet. These methods belong to the TL approach, iv) The AO strategy is presented to fine-tune the hyperparameters‟ accuracy. It comprises the basic hunting strategy of Aquila mathematically and presented the proposed algorithm in this strategy and v) the summary of this chapter is discussed with the comparison result.

Utilizing optimized transfer learning-based strategies for the automated classification of brain cancers is one potential new direction in the field of medical imaging. Brain tumor classification is a challenging task due to the complexity of tumor characteristics, variability in tumor shapes, and limitations in image acquisition techniques. Transfer learning is a technique that involves reusing pre-trained deep neural network models to perform a new task. In the context of brain tumor classification, transfer learning involves adapting pre-trained models for image recognition tasks on large datasets, such as ImageNet, to perform classification tasks on smaller medical image datasets.

Optimized transfer learning-based techniques aim to overcome the limitations of traditional deep learning approaches by fine-tuning pre-trained models with smaller datasets, thereby reducing overfitting and improving generalization performance. Furthermore, optimized transfer learning-based techniques often incorporate data augmentation techniques to further improve the model's ability to generalize to new data.Numerous studies have demonstrated the efficacy of optimized transfer learning-based approaches for automated categorization of brain tumors. For instance, Havaei et al. 2017) proposed a profound brain network model in light of move learning with pre-prepared VGG-16 and U-Net models. Wang et al. (used transfer learning and deep learning to 2019) developed an independent method for segmenting and detecting brain tumors. Glioma classification has previously been studied using optimized transfer learning-based methods. Cheng et al. () used very little training time to classify glioma images. 2018) came up with a transfer learning-based strategy that uses AlexNet models that have already been trained. Wang et al. (2019) developed a novel transfer learning approach for glioma diagnosis based on a deep neural network.

II. LITERATURE REVIEW

Cheng et al. (used very little training time to classify glioma images. 2018) came up with a transfer learning-based strategy that uses AlexNet models that have already been trained. In their study, they fine-tuned the pre-trained AlexNet models on a small glioma image dataset to classify glioma images into different grades. They also compared the performance of their approach with other state-of-the-art approaches, such as support vector machines and random forests. The results showed that their approach outperformed other approaches in terms of classification accuracy and sensitivity.

Similarly, Wang et al. (2019) developed a novel transfer learning approach for glioma diagnosis based on a deep neural network. They used a pre-trained Inception-V3 model, which was fine-tuned on a glioma image dataset to classify glioma images into different grades. To more readily get a handle on the discriminative parts of glioma photographs, they likewise utilized an element representation way to deal with show the model's learnt highlights. In terms of classification accuracy, their method performed better than other cutting-edge approaches.

Deng, Zhang, and Liu investigated the application of deep CNNs and transfer learning to the classification of brain tumors in 2018. To order X-ray photos of the mind into paired classes — glioma versus meningioma — the examination utilized a pre-prepared CNN model, VGGNet-16, and changed it utilizing the X-ray information. The findings demonstrated that transfer learning significantly improved the CNN model's performance, leading to an accuracy of 97.3% versus 90.9% in the absence of transfer learning.

Comparative examination was led by Yu, Gao, and Gu (2020), who researched the capability of move learning for X-ray based mind growth order. To characterize glioma, meningioma, and pituitary malignant growths, specialists used an assortment of mind X-ray pictures to calibrate four pre-prepared CNN models (VGG16, VGG19, ResNet-50, and InceptionV3). The highest accuracy of the CNN models, InceptionV3, was 95.23 percent, indicating that transfer learning significantly improved their performance.

Cheng et al. (used very little training time to classify glioma images. 2018) came up with a transfer learning-based strategy that uses AlexNet models that have already been trained. In their study, they fine-tuned the pre-trained AlexNet models on a small glioma image dataset to classify glioma images into different grades. Along with their method, support vector machines and random forests, two cutting-edge techniques, were also evaluated. Their method was found to be more sensitive and accurate than other methods.

Wang et al. (for the detection of gliomas) 2019) utilized a deep neural network to develop a novel approach to transfer learning. They used a glioma picture dataset to refine a pre-trained Inception-V3 model, which they then used to give glioma images grades. They also used a feature visualization technique to visualize the learned features of the model, which helped in understanding the discriminative features of glioma images. In terms of classification accuracy, their method performed better than other cutting-edge approaches.

Roy and Singh developed a novel transfer learning-based method for classifying brain tumors using DNNs (2021). A pre-trained DNN model, InceptionV3, was used to refine the binary classification of glioma and meningioma using brain MRI scans. The outcomes showed that the recommended strategy beat existing cutting edge methods with a high exactness of 97.14 percent.

Zeng, Zhu, Qin, and Shen (2018) also explored the application of transfer learning for glioma diagnosis using convolutional neural networks (CNNs). AlexNet, a pre-trained convolutional neural network (CNN) model, was used in this study to fine-tune a brain MRI image dataset for binary glioma and non-glioma classification. With an improvement in accuracy of 96.2%, the findings indicated that transfer learning significantly improved the CNN model's performance.

In another study, Yang, Sun, Wang, and Huang (2020) proposed a transfer learning approach for brain tumor classification using residual networks (ResNet). In this work, an already-trained ResNet model called ResNet-50 was used to classify brain MRI scans to see if they showed glioma, meningioma, or pituitary tumors. The findings demonstrated that, in terms of accuracy, sensitivity, and specificity, the proposed method performed better than previous cutting-edge approaches.

III. METHODOLOGY

3.1. TRANSFER LEARNING APPROACH

In ML, the TL approach includes applying a formerly prepared model to irrelevant issues. In TL, a machine's past assignments are taken into account when predicting how well it will perform on a new task. The previously learned ML model is utilized in TL for a brand-new but related issue (Lee et al. 2020). TL is a useful method for effectively learning characteristics that are repeated in another ML model. In this chapter, the main motive of the TL is to identify the variation among benign and malignant stages. These both stages have high similarity which consumes more time for prediction and classification. The TL is more significant in classifying among an equal stage and made it as a primary preference. Also, the weighted model is frozen and the final layers are modified for a dissimilar dataset in the TL strategy.

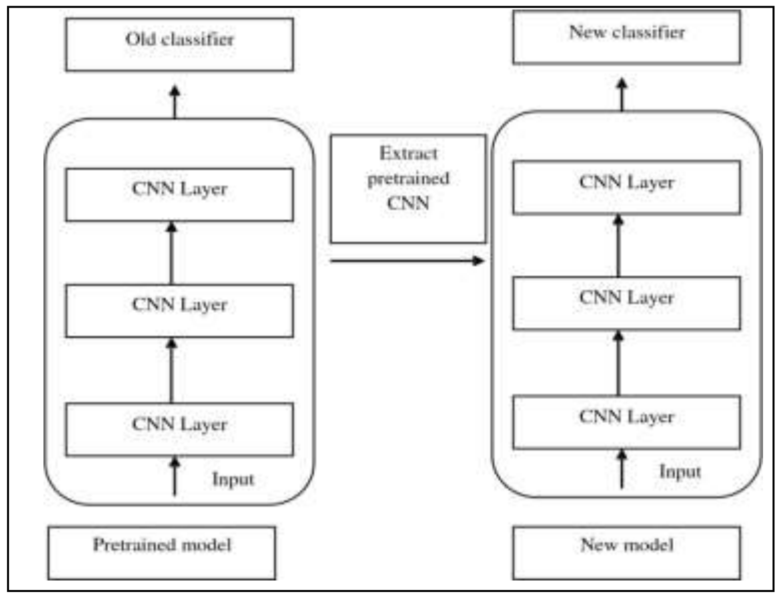


Figure 3.1 TL process

From above Figure 3.1, the old model is already pre-trained with an efficient ML model i.e., CNN. These CNN-trained results are fairly generated. But even for a highly accurate training, the previously trained CNN is again trained with the data using TL. This TL is majorly used for natural language processing which is the huge labelled dataset. These datasets require a high amount of expert knowledge. In addition, the training time is minimized due to the DNN implementation from the complex task that may require a couple of days or even a week. In the TL model, when it does not have any interpreted information to learn the model, then the pre-trained model is again learned with a similar task (Xenya et al. 2021). When Tensor Flow is used to learn the original method, it can be restored and retrained for a few layers. In the TL model, the features are worked and learned in the general task initially then it can be applied to an alternative activity. Also, the input model can be trained with a similar size to the first training.

3.1.2 Training A Model

Consider that we want to process Task A but there is a lack of essential data to train a DNN. To find a relevant task B, the TL method is required to process a huge number of data to get around it. Using the DNN model, task B is to be trained and then process the model to resolve task A. The problems that are used to solve will choose whether the entire model is developed or employed a few layers. When the inputs are similar in the task A and task B, then the model is to be reapplied and make a prediction for new input. The model is to be investigated for modifying and retraining the distinct task-specific layers and the output layer.

3.1.3 Using A Pre-Trained Model

You could use a model you've already learned. There haven't been many models to study in the past. The several layers are reused and retrained for identification of the task. Keras comprises nine pre-learned models used in TL for prediction and fine-tuning. It is used to demonstrate that the model can be used and discovered for relearning. DL models are mostly used to form a TL.

3.1.4 Features Extraction

In the TL processing, there is another option to utilize DL for identifying the optimum representation issues. This model comprises identification for the key features that are known as representation learning. It can generate significantly improved solutions than a representation of hand-designed. The ML-based Feature extraction is mainly implemented manually by researchers and domain experts as shown in Figure 4.2. The DL has extracted the features automatically. Also, the DL model does not reduce the feature engineering and domain knowledge importance in it. The DL has implemented a feature to be included in the network.

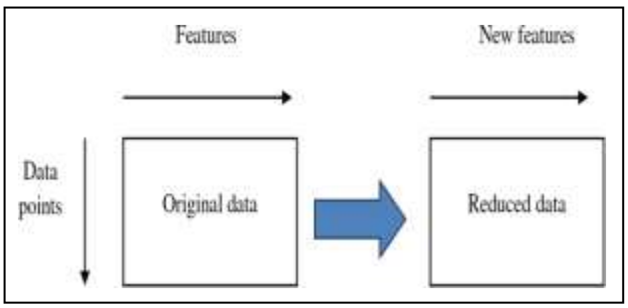


Figure 4.2 Size reduction using TL

The Neural networks have a learning ability to identify whether the features are critical or not. Even for many complex tasks, it would have required a lot of human effort. This can represent the learning model for finding a decent characteristics combination in a short amount of time.

The trained representation is applied for a variety of challenges. Simply it can be initializing the layers to determine the representation of an appropriate feature. Due to its being too task-specific, the network can misinterpret the output. Instead of it, transfer the data into the network, and output is processed through an intermediate layer.

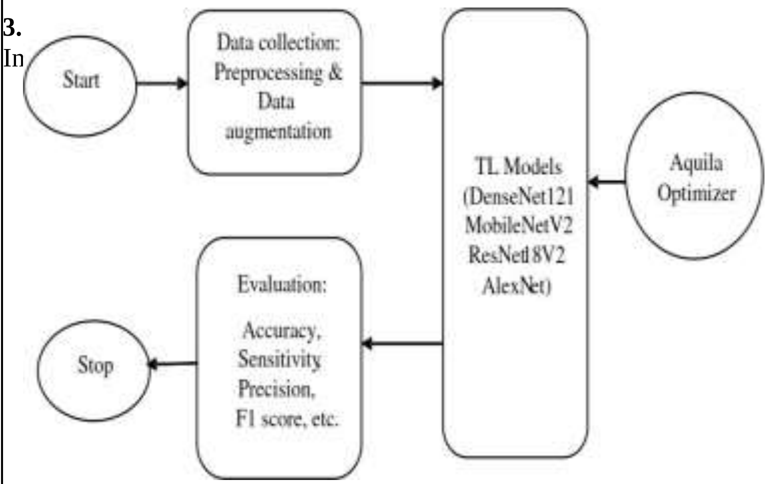
A layered structure could be inferred from the raw data. This model is widely used in computer vision due to its capacity to reduce dataset size and processing time. It additionally approaches the most ideal that anyone could hope to find exemplary calculations.

3.2 HYPERPARAMETERS OF LEARNING MODEL

In the learning model, the behavior and performance purely belong to hyperparameters. The primary objective of hyperparameter tuning in the learning model is to reduce a predefined loss function while also increasing efficiency. The hyperparameters models are classified into two types: network structure related and training related. The parameters relevant to network structure are hidden layers, kernel size, and type, padding, stride, and dropout. The parameters that are relevant to training are learning rate, batch size, momentum, and optimizer. These hyperparameters of TL models are fine-tuned using a metaheuristics model of Aquila Optimizer (AO). Thus, the proposed work of AO based TL method is to perform a classification for the brain tumor prediction. This is described inthe following section.

3.

In



the best values of TL hyperparameters. In Figure 4.3, we can see an undeniable level block design of the recommended AO-based Move learning model. The figure comprises various phases namely Pre-processing phase, Training and Classification phase, Optimization phase, and Performance evaluation phase.

Figure 3.3 The proposed workflow

3.3.1 Pre-Processing Phase

This phase carried image augmentation and collection processes like flipping and rotations. The pre-processing is explained in the introduction Chapter-1 which can be performed as a transformation of images.

3.3.2 Training and Testing Phase

It is the second phase of this work. This phase involved training and testing of data preparation of TL model for predicting four types of tumors. There are four various models that are evaluated to build the pre-trained CNN model which is known as the TL model. The TL models used in this work are AlexNet. DenseNet121, MobileNet and ResNet18V2 that is explained below.

3.3.2.1 AlexNet

In the year 2012, the AlexNet model was designed as the first CNN model in Deep Learning. When compared to the Lenet-5 model, this technique improves the network's depth. The AlexNet is a type of CNN based TL method that is given in Figure 3.3. In this AlexNet, it has both an input and classification output in it. These data are pre-learned whereas a few layers are shifted directly without any development from the primary source that is why AlexNet is called as a TL. This model is a pretrained AlexNet classifier that can be used to obtain an accurate classification (Hao et al. 2021). The AlexNet structure is used to learn the dataset that belongs on its weights, biases, and some other parameters of training. These parameters are known as hyperparameters.

Figure 3.3.2.1 shows the structure of AlexNet. The entire AlexNet structure consists of maximum pooling layer, five convolutional layers, and three fully-connected layers. The AlexNet has an input layer of size 227×227×3 and obtains a width and length of 227 with 3 RGB channels in the 2D image. To demonstrate an AlexNet learning performance, the non-saturating activation functions namely sigmoid, ReLU and tanh are implemented. Finally, the Fully Connected layer at 2048 size is changed with 1000 number of classes into the classification layer. Therefore overall, AlexNet comprises of eight layers with feature learning. There are five layers in the ReLU activation function and convolutional layers and also it has a three pooling layers. In an output layer, the softmax activation function is utilized. Thus, an entire architecture comprises an overall number of 62.3 million parameters.

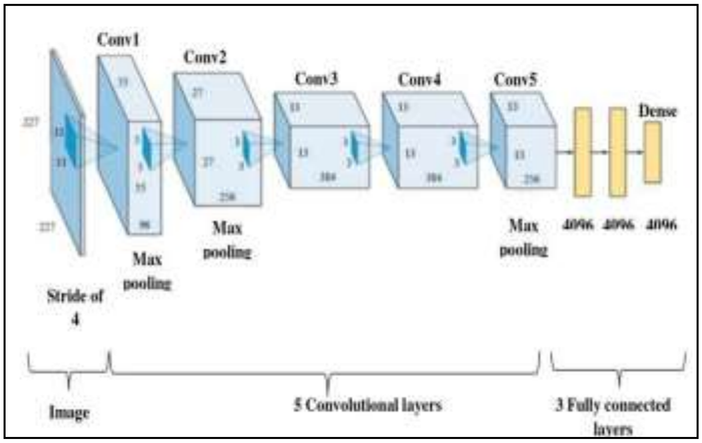


Figure 3.3.2.1 Structure of AlexNet

The learning of an AlexNet is used to be scheduled through TL. The hyperparameter fine-tuning is pre-trained to calculate the best solution. The hyper parameter fine-tuning of weights and bias control the AlexNet precision. The fine-tuning of AlexNet is performed with some other layers that are already set with an accuracy rather than training a Neural Network method from scratch. This method of tuning is very simple which is the main benefit of an AlexNet. In the AlexNet model, the conventional CNN method has been tuned with the hyperparameters in the process of layer by layer. This model is fitted with a 22 layers depth which would not obtain an inaccurate learning challenge on large-scale learning samples.

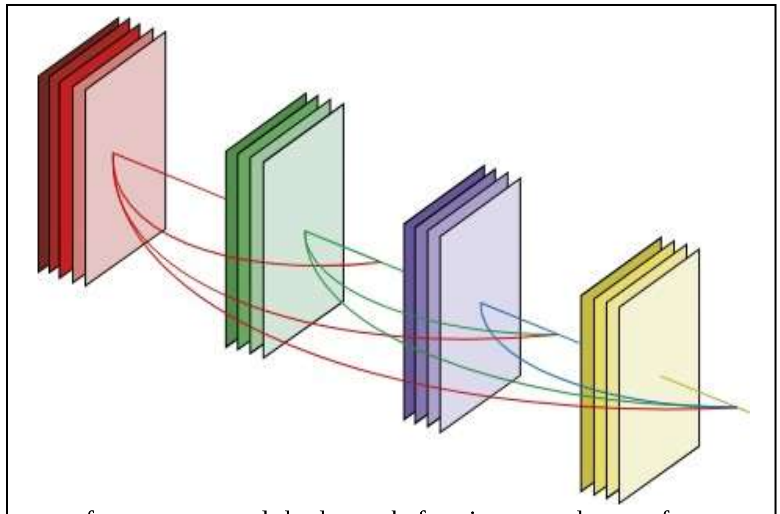
During the CNN training process, the biases or weight parameters are evaluated to improve the accuracy of classification. To construct a highly precise classification, the CNN hyperparameters should be learned. The CNN hyperparameters are the variables that can be determined by an extremely efficient network. These hyperparameters of AlexNet has been divided into training-based hyperparameters and structure-based hyperparameters. As a result, the structure-based parameters are the number of hidden layers and units, network weight, activation function, and bias drop out. Momentum, Batch size, Learning rate, and Number of epochs are the training-based parameters.

3.3.2.2 ResNet model

There are 18 layers of convolutional neurons in the ResNet-18 network. Computers, office supplies, and animals are among the 1,000 item categories that the pre-trained model can identify. Consequently, the network has acquired the ability to represent a wide range of images using a comprehensive set of features. The greatest info size for the organization is 224x224 pixels. The structure of the ResNet model is discussed in proposed workflow

3.4.2.3 DenseNet model

The DenseNet is also a significant technique on deep CNN. A novel kind of connectivity is used in this procedure. This kind of connection works with any and all network layers that are already in place. As a result, the current layer is used to get an



output feature map, and the layers before it are used to get features. This link eliminates the drawbacks of the vanishing gradient and allows for the formation of more features with a smaller convolution kernel.

Figure 3.3.2.2.1 DenseNet structure

The basic block of unit modules in the DenseNet structure is shown in Figure 3.3.2.2.1. The DenseNet model has a quadratic growth rate and four completely linked, closely spaced layers. It is sent into each resulting layer as a contribution of the component that was produced by the layer beneath it. A single residual layer is created by combining the feature map from the layer before it and the residual unit from ResNet. This network model's objective is to enhance the feature maps of the subsequent layers. From that point onward, a pixel esteem in the component maps is traded out and it is included with everything else.

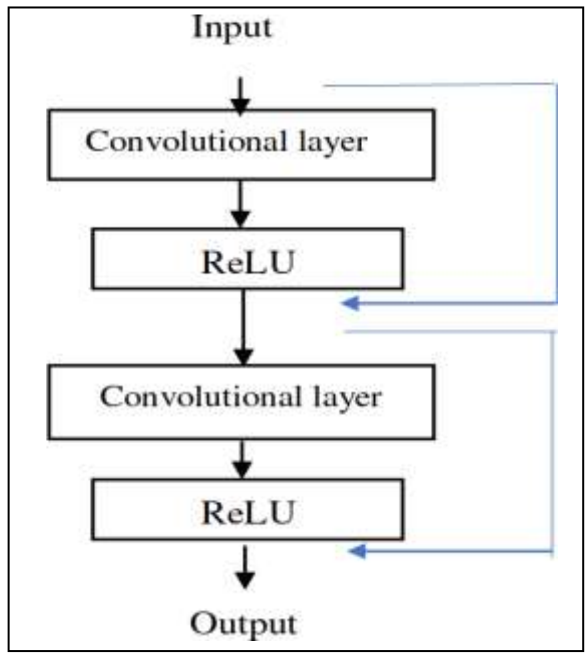


Figure 3.3.2.2.2 Dense connected module

Figure 3.3.2.2.2 Dense connected module Figure 3.3.2.2.1 shows that the previous convolution layer-based feature

A substantial module houses maps. With the assistance of these modules, the number of feature maps that are accessible can be increased. The hyper parameter growth rate is applied to the numerically equivalent magnitudes xi and xi+1 in order to regulate the total number of feature maps. Consequently, we use the hyper parameter growth rate to generate Xi+2 as each network layer's output. In order to achieve superior results, every convolution layer and an additional dense block layer are utilized.

3.3.2.4 Mobile Net model

The Mobile Net model is a simplified framework with depth-wise separable convolutions. A light framework for deep convolutional neural networks is the outcome (Arbane et al.). 2020). the most widely recognized utilizes for this plan design are versatile and installed programming. The structure of the Mobile Net model as a depth-wise separable filter is shown in Figure 3.3.2.4

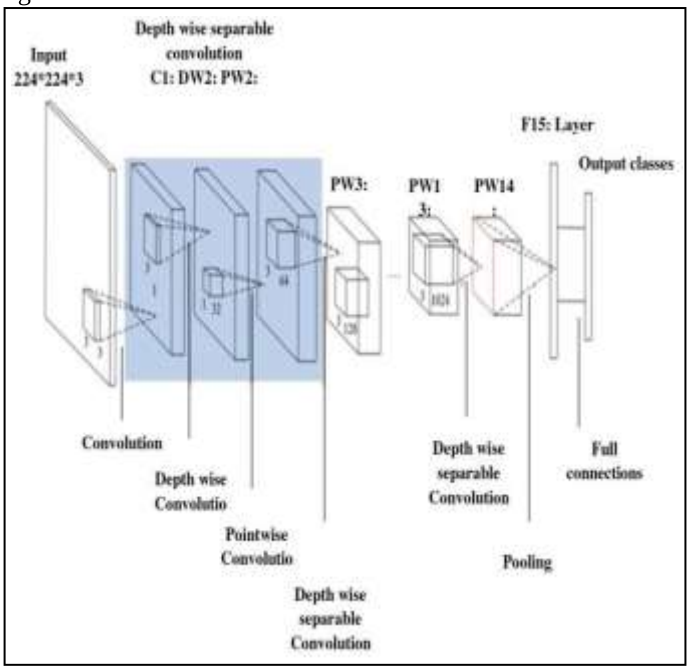


Figure 3.3.2.4 MobileNet architecture

The MobileNet architecture shown in Figure 3.3.2.4 consists of depth-wise separable convolutions instead of a conventional convolution layer which is used for a lighter model. Profundity wise detachable channels and point convolution channels make up the distinguishable convolutions channels. The process of separable convolutions in depth-wise filters is ideal convolution on each input channel. The point convolution filters are output of depth-wise separable convolutions that provided a $1 * 1$ convolution in linear. MobileNet comprises extra width multiplier hyperparameters and resolution multiplier hyperparameters for varying the accuracy and speed of the model. These are convolution layers that can be separated by depth and can be changed for specific tasks.

Every depth-wise separable convolution layer contains the point-wise convolution and a depth-wise convolution. These layers are the individual layer of depth-wise separable convolutions. As a result, the MobileNet has 28 layers including depth-wise separable convolutions. In the MobileNet, there are a total number of 4.2 million parameters processing. These parameters are reduced by adjusting the width of the multipliers as well as modifying the inverted residual blocks, linear bottlenecks, and ReLU activation. These modifications of blocks are provided with various variants named as MobileNet-v1, MobileNet-v2, and MobileNet -v3.

3.3.3 Optimization Phase

The optimization phase comprises a hyperparameter tuning of TL models using AO algorithm. Finally, the proposed model is evaluated in comparison to other models. By applying an AO model, the accuracy of a TL classification is attained. In the following section, the AO model is discussed with its basic inspiration.

3.3.3.1 Aquila Optimizer (AO) model

In recent times, all applications are switching to an optimization method due to its problem-solving behaviour. The optimization method is used to choose the best solution among entire solutions. A meta-heuristic model is a tool to provide decision-making when an accurate solution cannot be processed. In the meta-heuristic model, there are many real-time issues that are solved without any complexity. Therefore, an Aquila Optimizer-based meta-heuristic model is the recent method that can be able to solve an issue effectively (Abualigah et al. 2021). The AO model is based on the hunting behaviour of an Aquila that is given in the following section.

3.3.3.2 Motivation of Aquila hunting behaviour

The Aquila is frequently regarded as one of nature's finest raptors. The Northern Hemisphere is where the Aquila is most frequently observed, and it is typically found in the family "Accipitridae". The Aquila looks like a dark brown colour naturally and it has a slight Golden-brown feather in the back neck. In the young age of Aquila, it mostly seems to be in white colour and its tail also looks white. The wings appear as a minor white mark. It has huge agility and higher speed normally and also has a sturdy foot too. The Aquila has very sharp fingernails for grabbing its prey such as squirrels, rabbits, deeps, hares, birds, and some ground animals. The Aquila has a unique behaviour compared to any other bird that is observed generally.

The Aquila has a high-flying capability to move high up to 200 km. It is always used to nest in mountains and in some additional high regions. The Aquila is used to breed in the season of spring and a steady-state. The Aquila generally lives for a long year or probably for its entire life. The female Aquilla on her pregnancy used to lay four eggs. All these eggs are incubated within 6 weeks and a few incubations happen in 12 weeks. The Aquila has higher confidence to fall from the mountain and also jump over one to another building. They can also travel for a huge territory for themselves.
In the hunting behavior, the male Aquila is used to hunt its prey solo. The Aquila used its sharp talons and speed for hunt. The Aquila often used to hunt prey like rabbits, squirrels, hares, and a few animals. The hunting strategy of Aquila followed four steps where every step has a distinct difference. The hunting strategy showed the Aquila‟s cleverness, speed, and ability. The Aquila used to move a back-and-forth motion for hunting based on the situation. There were four phases to the Aquila's hunt: a high soar followed by a vertical stoop, a contour flight followed by a brief glide attack, a low fly's gradual descending attack, and finally, climbing up on the target and taking it in.

The primary method of hunting is the high soar with a vertical stoop. The Aquila would then select its prey and pursue it as it flew. Aquila begins by flying in the upper regions while ascending over the lower ones. After finding the prey, the Aquila is used to get nearer to the prey with a low angle position. This low angle can minimize the distance between Aquila and prey. The Aquila travel at a low slight angle with higher speed as the wings close. This speed and catching ability are the main features of hunting prey successfully. As of now, the aquila spreads its wings and tail and uses its feet to push and hold onto the prey in a moment.
The brief glide attack contour flying comes next. This hunting

strategy is different from the first step. In this hunting, the Aquila used to fly a little bit higher to the ground. It flies at a low level and searches prey closely. When it sees the prey, it suddenly grabs the prey with its talon while flying. The prey cannot protect from the strong grab of Aquila. This hunting is possible for prey like seabirds, ground squirrels or breeding grouse, and so on.

A slow, low-flying descent is the third hunting tactic. Here, the Aquila goes as far as the ground and dispatches a sluggish, purposeful attack on its objective. Before swooping down and landing on the animal's neck or back, the Aquila will carefully select its prey. It would abruptly drive its nail into the victim's flesh. This hunting strategy works well with snakes, hedgehogs, tortoises, foxes, and other slow-moving animals.

The final strategy is walking and grabbing the prey. This hunting strategy is used to hunt prey by its walk on land. The Aquila walks on the ground just like that and suddenly grabs and pulls the prey. This hunting method is applicable for prey like young deer or young sheep in its group.

On studying the Aquila's hunting behavior, it showed the skill and cleverness of its intelligent hunting. This type of hunting is often done by a human but an Aquila is better than a human. According to this study, the mathematical AO model based on TL is derived to perform a hyperparameter tuning.

3.3.3.3 Solutions initialization

The initialization is the first step to initialize a population. The population are generated randomly using the candidate solutions (S) that is expressed in Equation (5.1). This method is formed stochastically between a lower bound (LowB) and upper bound (UpperB) of a problem. The best solution is found out using an optimal result for each iteration.

$$S = \begin{bmatrix} S_{1,1} & \cdots & S_{1,j} & S_{1,D-1} & S_{1,D} \\ S_{2,1} & \cdots & S_{i,j} & \cdots & S_{2,D} \\ \vdots & & & & \vdots \\ S_{N-1,1} & \cdots & S_{N-1,j} & \cdots & S_{N-1,D} \end{bmatrix}$$

where, S represents the current pool of possible answers found by chance,

represents positions of the ith solution,

D represents a dimension size of the problem and

N indicates an overall quantity of population.

$$S_{ij} = r \times \left(UpperB_j - LowB_j\right) + LowB_j, \text{ i=1,2,...N, j =1,2,...}$$

where, r represents a random number between 0 and 1 which follows uniform distribution.

represents jth lower bound

$UpperBj$ represents jth upper boun

IV. RESULT AND DISCUSSION

The several recent works that are applied in the medical field using imaging techniques. There are numerous works developed using DL and TL methods.

It has a unique section that constitutes the DL model applied for a brain tumor. This section showed the DL model's responsibility and importance in brain tumor prediction. Also, to obtain an optimal result, there are many DL methods combined with the metaheuristics model. The fusion of DL and optimization model is applied for brain tumor datasets and provided a greater result. Likewise, there are many ideas presented based on the TL and optimization models which is more helpful and supportive for this thesis idea. The efficient strategies are provided with hybrid methodologies, DL, and TL models for performing a segmentation and classification process.

4.1 PYTHON BASED IMAGE PROCESSING

Image processing is used to process the transformation and manipulation of multiple images at a time. Similarly, it is used to extract useful data from the transformed data. Image processing is a broad application that can be implemented in all fields. In this thesis, image processing is implemented using Python. Python is one of the most advanced programming languages in the current generation which is very efficient for image processing. The python has provided amazing inbuilt libraries in it. The python tools are used to obtain image processing operations very efficiently and quickly.

A few image processing libraries that are provided by Python are given in the following.

- OpenCV – For an Image processing library, it is generally concentrated on real-time digital visions. These visualizations are applicable for a wide range of applications such as 2D and 3D feature toolkits, face recognition, gesture recognition, Mobile robotics, Human-computer interaction, Object recognition, and others.
- Numpy and Scipy libraries – These libraries are used for image manipulation operations.
- Scikit – it is a library that is used to provide a lot of ML and DL algorithms to perform image processing.
- Python Imaging Library (PIL) – This library is used to process basic functions on image processing. Some of the basic features are creating thumbnails, rotation, resizing, converting among several file formats, etc.

Basic functions to perform image processing in python are given in the following,

Install required library: Initially install the essential library for image processing such as OpenCV, Python Imaging Library (PIL), and so on. To install a library file, use pip to process the necessarylibrary.

- Open () and show() function of Image: Next, the process is to perform basic operations such as opening the file/image and showing the function to view an image. Also, the images can be rotated in it.
- Convert and Save () Image: After that, the file format of images can be modified from one to another form.
- Resize-thumbnails (): To modify image size, use a thumbnail () method of pillow library.
- Converting to grayscale image: By using a function convert (), the original input images can be converted intoa grayscale image.

4.2. Python IDLE-3.10

To implement image processing in python language, the python IDLE software tool is used. The IDLE refers to an Integrated Development and Learning Environment or is also known as Integrated Development Environment (IDE). Python provides a default installer of IDLE for the Windows operating system. The IDLE is not accessible in the Python installer by default for Linux operating system. In Linux, it is required to install the individual package managers.

The IDLE is executed in a single statement such as Python Shell. It can be used to create, execute and modify Python scripts. The IDLE is used to execute a fully-featured text editor to generate a Python script. This script involves features such as autocompletion, syntax highlighting, and smart indent. The IDLE is also used to debug with features of breakpoints. The IDLE is an efficient tool for image processing that leads to provide an exact output for the required application.

4.3. PERFORMANCE METRICS

In this work, the proposed methodologies are evaluated and compared using several performance metrics. These metrics are used to estimate the performance of the network model. Some of the considered metrics are F1Score, sensitivity, specificity, accuracy, precision, IoU coefficient, and Hausdorff Distance (HD). These metrics provide an appraisal for the performance of proposed methodologies against previous segmentation and classification methods. At First, the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are to be evaluated by comparing predicted Image (PI) and Ground Truth image (GT) that are defined below.

True Positive (TP): the pixel value of GT and PI has one

False Negative (FN): it provides a pixel value of GT as one and for the pixel value of PI is zero.

False Positive (FP): it provides a pixel value of GT as zero and c and for the pixel value of PI is one.

True Negative (TN): the pixel value of GT and PI has zero.

The pixel values of both GT and PI evaluations are used to calculate the value of Accuracy, sensitivity, specificity and F1 Score values. Sensitivity is defined as the estimation of number of TP and FN. It is used to evaluate the proportion of real positives for recognition and is expressed in the following Equation (4.3).

$$\text{Sensitivity or recall} = \frac{\text{Tp}}{\text{Tp+FN}} \quad (4.3)$$

Specificity is defined as the estimation of number of TN and FP. It is used to evaluate the proportion of real negatives for recognition and is expressed in the following Equation (4.3).

$$Specificity = \frac{TP}{TN+Fp} \quad (4.3)$$

The precision metrics is defined as the estimation of number of TP and FP. It is used to evaluate the proportion of real positives for the recognition and is expressed in the following Equation (4.3).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (4.3)$$

The Accuracy is defined as the proportion of exact predictions to total predictions and is expressed in Equation (4.4).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP TN+FN}} (4.4)$$

The F1score is the harmonic mean of precision and recall and is expressed in the following Equation (4.4).

$$\text{F1 Score} = 2 * \frac{\text{Precision*recall}}{\text{precision+recall}} (4.5)$$

The F1score is the harmonic mean of precision and recall and is expressed in the following Equation (4.6).

$$\text{IoU} = \frac{\text{TP}}{\text{TP+FP+FN}}$$

Hausdorff Distance (HD) is defined as the estimation among the boundaries of the PI and GT results. The predicted output will be having a minimum HD and higher Dice similarity and is expressed in the Equation (4.6).

V. COMPARISON ANALYSIS

5.1 SSA Based Bidirectional CONVLSTM U-NET Segmentation And Hybrid Classifier Model

The proposed work is categorized into two. One is for segmentation and another work is for classification. The SSA-based bidirectional ConvLSTM U-Net model is presented for brain tumor segmentation in Chapter 3 of this thesis. Also, the Hybrid ResNet and Inception-v3 model is presented for brain tumor classification in Chapter 3. The experimental verification is evaluated in this section by using a BraTS 2018 database.

The efficiency of this bidirectional U-Net model is evaluated and compared in this section. The BraTS 2018 is the dataset collection that has a multi-institutional pre-operative MRI dataset for gliomas-based brain tumors segmentation. Gliomas are brain tumors that vary in shape and appearance. The BraTS 2018 involved a patient of 66 unlabelled themes to validate the dataset. In the training phase, the dataset provided 335 patients affected in glioma tumor. In the patients, 259 patients are in the high-grade glioma (HGG) cases and 76 patients are attained a Low-Grade Glioma (LGG) case.

- **Segmentation Result of SSA based Bidirectional ConvLSTM U-Net Model**

In the intratumor, it is classified into edema region, necrotic region, and enhancing region of tumor. The non-enhancing tumor region is clustered into affected regions. In Figure 5.1, the experimental result shows the brain tumor segmentation.

From Table 5.1, it showed the measured metric values of sensitivity, specificity, F1score and accuracy for the SSA based bidirectional ConvLSTM U-Net model and traditional methods like Particle Swarm Optimization (PSO), Whale Swarm Optimization (WSO), Glow Swarm Optimization (GSO), Brain-Storm Optimization (BSO), and Fuzzy BSO (FBSO) respectively.

Table 5.1 Performance comparison of proposed method with other optimization techniques

Methods	**Sensitivity**	**Specificity**	**Accuracy**	**F1 Score**
PSO	87.77	78.38	84.33	89.66
WSO	92.11	85.29	89.67	92.9
GSO	89.6	79.78	86	90.63
BSO	92.9	87.88	91.16	93.81
F-BSO	94.39	88.96	93.85	95.42
SSA based bidirectional ConvLSTM U-Net	96.6102	92.4242	94.4	94.21

Table 5.1: Measured Metric Values

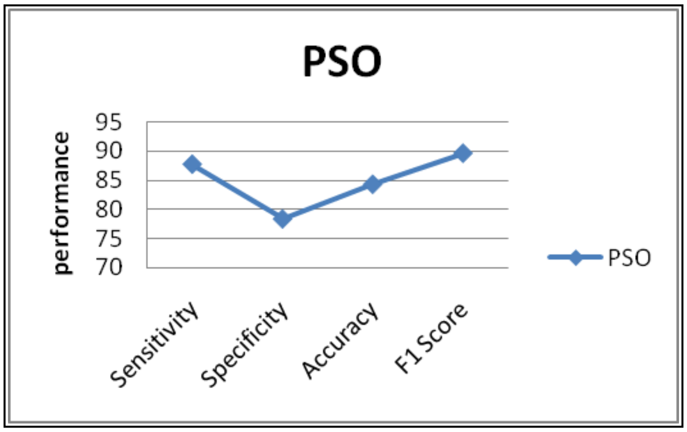


Figure 5.1(A): PSO

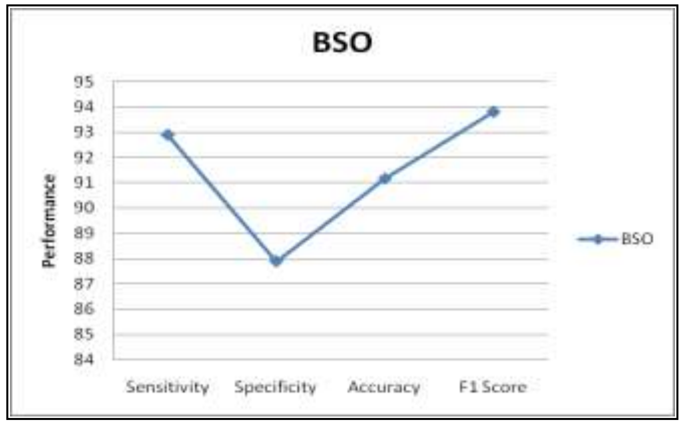


Figure 5.1(C): GSO

Figure 5.1(B): WSO

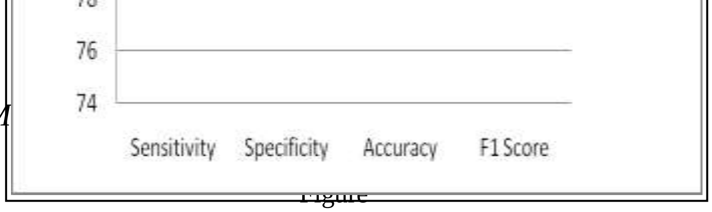


Figure 5.1(D): BSO

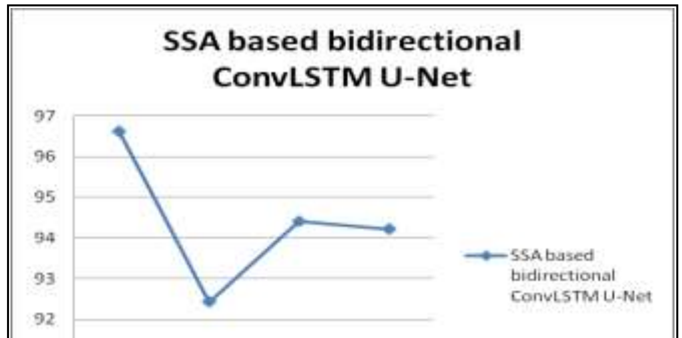


Figure 5.1(E): SSA Based Bidirectional ConvLSTM-U Net

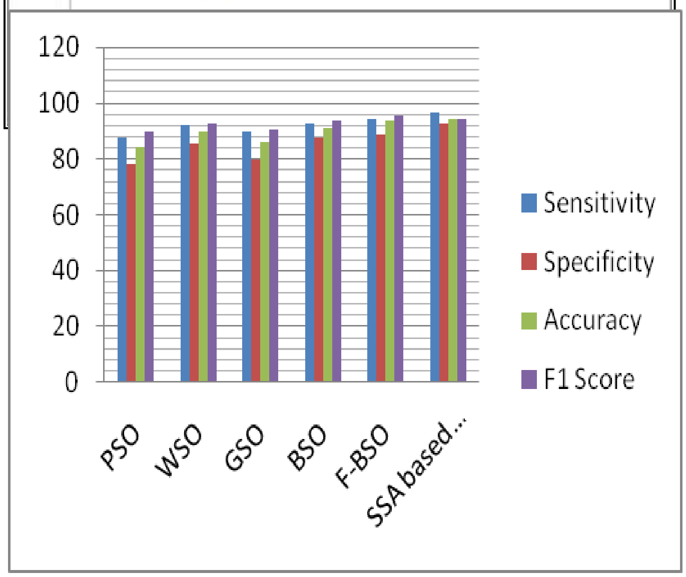


Figure 5.1 Performance comparison of proposed method withother optimization techniques

The performance of specificity, sensitivity, accuracy, and F1score rate increased considerably due to the inclusion of LSTM layers and attention gates.

5.2 Classification Result of ResNet and Inception Net model

The classification result of the proposed Hybrid ResNet and

Inception Net model is presented. These classification results are compared against the conventional models like CNN, Enhanced Capsule Networks (ECN) (Afnan et al. 2020), traditional ResNet model (He et al. 2016) and Kernel Extreme Learning CNN (KE-CNN) (Pashaei et al. 2018). These results are plotted and varied below 500 numbers of epochs with step size of 100 epochs.

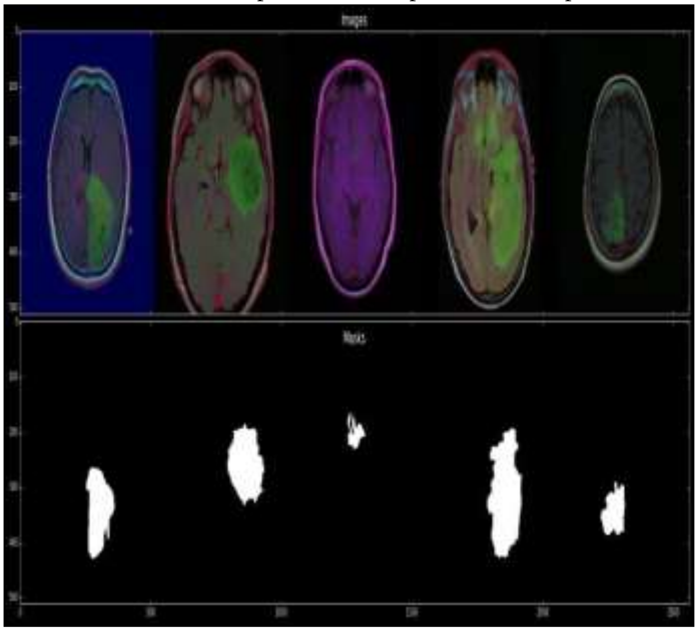


Figure 5.2(A) - Result Images- ResNet model

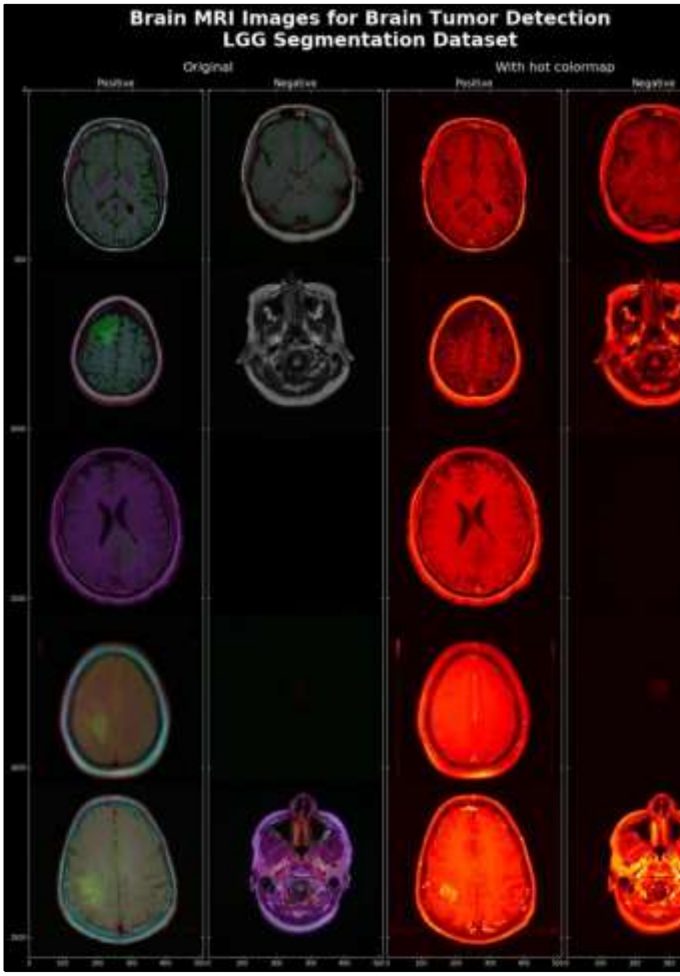


Figure 5.2(B)- Result Images- Inception Net model

Similarity coefficient's (X, Y)	Actual formula
Dice coefficient's	$2 \frac{\mid X \cap Y \mid}{\mid X \mid + \mid Y \mid}$
Cosine coefficient's	$\frac{\mid X \cap Y \mid}{\mid X^{41/2} \mid . \mid Y \mid^{1/2}}$
Jaccard coefficient's	$\frac{\mid X \cap Y \mid}{\mid X \mid + \mid Y \mid - \mid X \cap Y \mid}$

Table 5.2- Three Similarity Coefficient

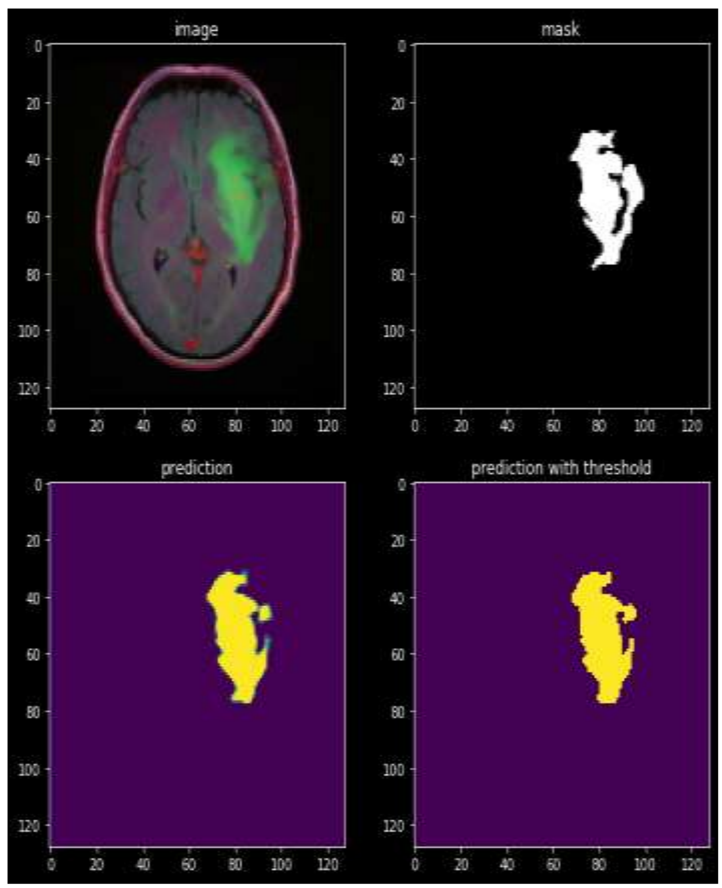


Figure 5.2(C) - Predicate Threshold of image

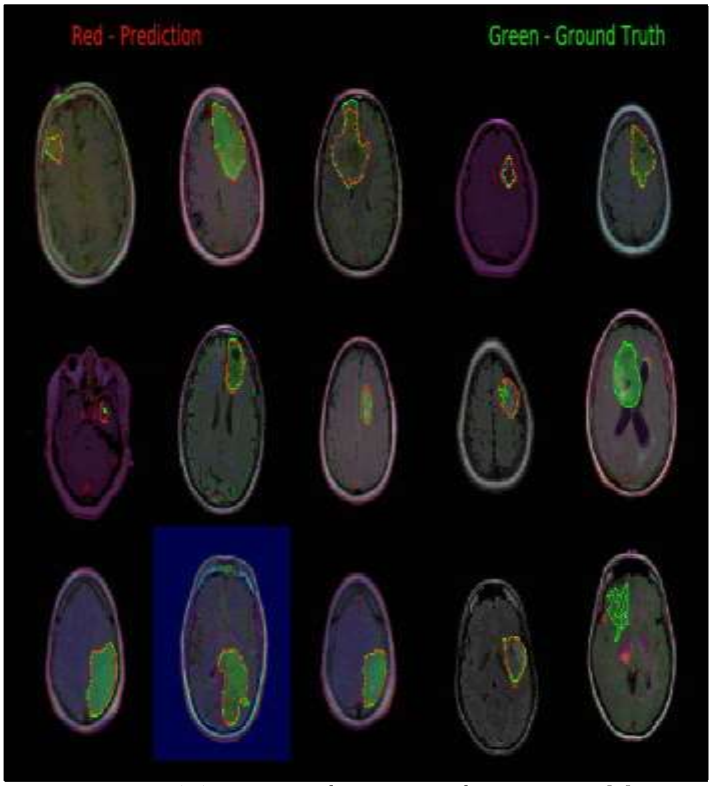


Figure 5.2(D)- Measure feature& performance model

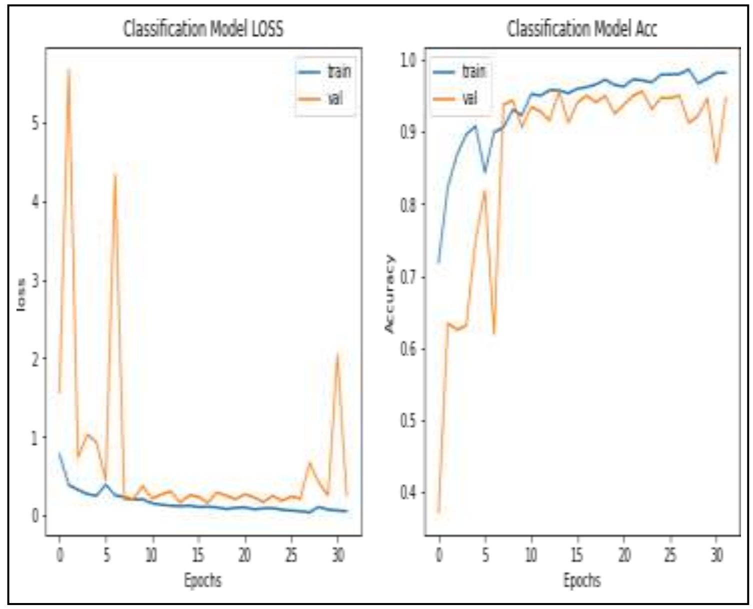
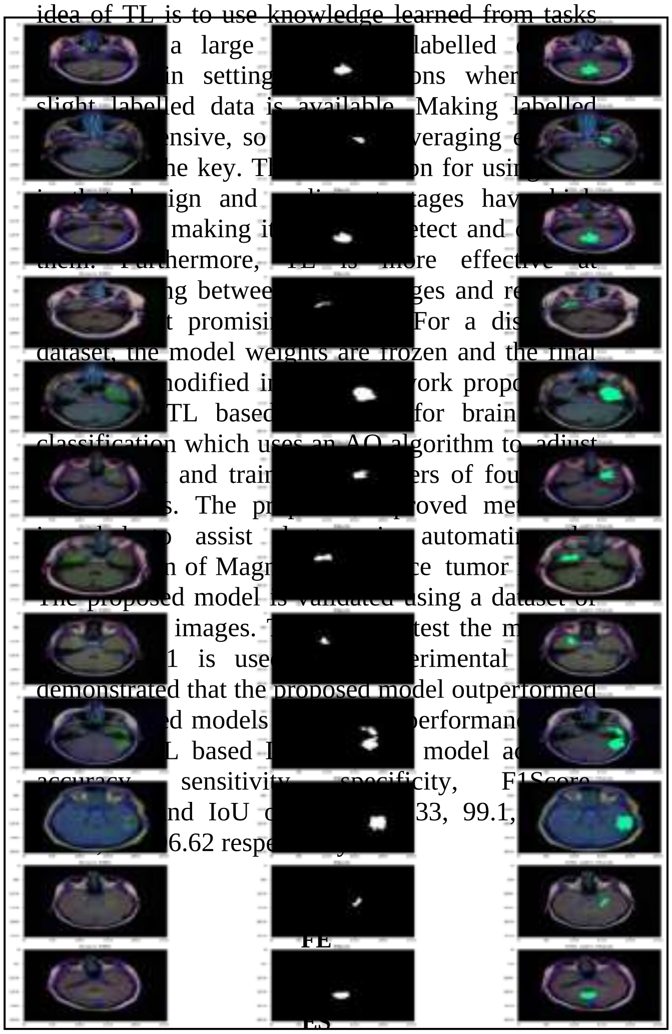


Figure 5.2 (E): Graph Loss Vs Accuracy

Figure 5.2(D)- Comparative studies of different images

VI
CO
NC
LU
SIO
N

TL is a powerful machine learning approach that reuses a learned feature in another. The common idea of TL is to use knowledge learned from tasks



a large ... labelled ... in setting ... ons wher ... slight labelled data is available. Making labelled ... ensive, so ... veraging ... he key. Th ... on for usin ... ign and ... ages hav ... making it ... tect and ... them. Furthermore, TL is more effective at ... g betwee ... ges and re ... t promisi ... For a dis ... dataset, the model weights are frozen and the final ... odified i ... ork propo ... TL based ... for brain ... classification which uses an AO algorithm to adjust ... and trai ... rs of fou ... s. The pr ... oved me ... assist ... automati ... n of Magn ... e tumor ... The proposed model is validated using a dataset of ... images. T ... test the m ... 1 is use ... erimental ... demonstrated that the proposed model outperformed ... d models ... erforman ... L based ... model ac ... accuracy, sensitivity, specificity, F1Score ... nd IoU ... 33, 99.1, ... 6.62 respe...

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