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Detecting Brain Tumor Stages using Convolutional AutoEncoder (CAE) with Hybrid Deep Learning Method

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***Abstract* -The Brain Tumor (BT) is the formation of abnormal brain cells, few of which can develop into cancer. Early and prompt detection of disease and development of treatment strategies improve patients' wellbeing and life span. Models are created using Deep Learning (DL) and Magnetic Resonance Imaging (MRI) to classify and diagnose brain tumours. This facilitates the effortless detection of brain tumours. The BT is usually caused through abnormal brain cell proliferation that damage the brain structure as well as eventually resulted in various stages of BT. Early BT discovery as well as timely treatment have reduced the mortality rate. Consideration of deep structure for analysis that have been used in both non-linear feature extraction and unsupervised learning, which relies significantly on the Autoencoder (AE). This transfer learning is utilized to obtain better accuracy. Applications for the AE and its variations have been effective in many domains, including recommender systems, data production, pattern recognition, and computer vision. Moreover, the Convolutional AE (CAE) toolkits are addressed for better performance in detection of the brain tumor. The goal of this research is determining whether DL methods can be utilized to automate the detection process. This work uses Convolutional Neural Network (CNN) with VGG19 as the hybrid model to provide the better or maximum accuracy of 92.39% than the traditional Convolutional Neural Network (CNN) with VGG19. This study objective is to use TL with hybrid CNN techniques through this assessment and analysis to direct researchers and medical experts towards effective BT detection systems.**

Keywords: ***Deep Learning, Autoencoder, brain tumor, Convolutional Neural Network, image processing, CNN with VGG19, Convolutional Autoencoder.***

I. INTRODUCTION

The diagnosis and treatment of conditions related to the brain depend on the identification of brain tumours, which is an essential part of medical imaging. Conventional tumour detection procedures include the manual evaluation of medical images, which may be laborious and susceptible to human errors [1]. Auto Encoder (AE) are fundamental building pieces that may be used to create hierarchical deep models, which are useful for organizing, compressing, and extracting high-level features even in the absence of labelled training data. Non-linear feature extraction and unsupervised learning are made possible by it. Some historical settings exist for the AE. Numerous researches have been conducted in the area of AEs based on DL. Nonetheless in accordance with the best knowledge, there aren't many studies have effectively positioned the ongoing work and advancements in this field. While several scholars have tried to formalize this field of study, few have made an in-depth summary of the present efforts or expanded on the unresolved issues [2]. The objective of this research work is to offer a thorough outline of the state-of-the-art research on AE-based DL and to suggest future directions in this field, due to the potential and emerging use of AEs in CNN approach. Due to their increased accuracy and significantly lesser risk for patients, image modalities are currently gaining popularity among radiologists. There are several ways to record medical imaging data, including radiography, echocardiography, tomography, and MRI. The most well-known of these is MRI as it produces radiation-free, better resolution images. By using non-invasive MRI, radiologists can identify brain disorders by gaining valuable insight into medical picture data [3]. Conversely, brain tumours can be identified early and without the need for human intervention in accordance with Computer-Aided Diagnosis (CAD) technique. A radiologist can get instructions from CAD systems and receive diagnostic findings using MRI images [4].

However, new prospects for the automated and accurate identification of brain tumours have been made possible by the rapid advancement of DL techniques, notably in the field of computer vision [5]. DL algorithms such as CNNs have demonstrated incredible results in image analysis processes including object recognition and segmentation. With the use of DL techniques, researchers have been looking at the viability of these approaches for the identification and classification of BT by MRI data [6]. To improve medical diagnosis and treatment outcomes, researchers are working hard to develop CNNs that can accurately diagnose and categories brain tumours and other types of medical imaging [7]. DL has the advantage of not requiring explicitly rule-based approaches or hand-crafted features can learn complicated, hierarchical characteristics right from unrefined data. CNNs are especially well-suited for medical image processing tasks and are designed to capture spatial relationships and local patterns within images. This has led to the development of DL as a very practical method for medical image interpretation. Compared to traditional methods, it may be used to identify irregularities in imaging data and provide more accurate diagnoses of disorders.

The original image has been utilized as an input in DL algorithms to overcome this problem [8]. To put it simply, they may be classified without the need for manually created characteristics. CNN are DL models that offer several convolution layers [9] that enable automated feature extraction from pictures [10]. When dealing with a big dataset, which is difficult to get by within the medical imaging industry, CNN worked well. The TL is one way of solving this problem. A model is previously trained using a sizable dataset associated with a different domain is utilized for classification purposes in transfer learning [11, 12]. Considering a limited dataset, the model benefits from this information in order to attain high accuracy. This research, offer two DL models-based system for automatically categorizing brain tumours. Using a fine-tuned model developed with an accessory to the TL driven VGG19 architecture, normal and diseased brain images are classified. Throughout the tuning process, three Fully Connected (FC) dense layers are used in term of the complete connected layers and BT are identified by employed in the last dense layer, which has an activation function as softmax. The 2D matrix is transformed into a vector by researchers using Global Average (GA) pooling 2D in behalf of flattening layers. This research work focuses on TL using CAE with hybrid CNN as CNN-VGG19 layers for improving the prediction of the BT detection.

II LITERATURE REVIEW

This research has considered the literature support of the hybrid DL method and the importance of AE in improving the performance of the prediction in medical field. Amin et al. offered a DL approach for brain tumour detection that use the ResNet50 architecture [13]. A collection of brain MRI images was used as the input to train the model, and the scientists employed transfer learning by employing the pre-trained weights of ResNet50. Combining gradient descent optimization with binary cross-entropy loss allowed the model to detect brain tumours with an amazing 92% accuracy. This worked better than traditional approaches and showed the potential of DL -based technology in clinical applications. Sarah Thompson et al. employed an ensemble strategy that included several CNNs to enhance the detection of brain tumours [14]. The authors used various architectures, including ResNet50, VGG16, and InceptionV3, to train individual CNN models. When detecting brain tumours, the ensemble model achieved a 94% accuracy rate. This was achieved by using a voting method to combine the predictions of several models. The ensemble approach performed better and was more persistent than using a single model, which suggests promising opportunities for improvements in diagnosis.

Brown et al., focused their efforts on radiomic features together with DL techniques to classify brain tumours [15]. Brown et al., used a combination of more conventional machine learning techniques and a deep neural network, specifically ResNet50, to classify tumours. Brain MRI data was utilized to extract and apply the quantitative radiomic properties. The suggested method had an 88% overall accuracy in classifying brain tumours into their respective categories. Accuracy and discriminating power of tumour categorization increased with the use of radiomic and DL features, offering valuable information for customized therapeutic approaches. Jennifer et al., used the ResNet50 and U-Net architectural frameworks to create a hybrid model for brain tumour segmentation [16]. In the study, the first coarse segmentation was done using U-Net, following fine segmentation was done using ResNet-50. A sizable dataset of hand-annotated brain MRI images was utilized in training the model. Experienced radiologists provided the annotations to the dataset. The hybrid model developed achieved 0.92 in Dice Similarity Coefficient (DSC), indicating the high degree of accuracy and precision in brain tumour segmentation. Treatment monitoring and preparation was facilitated by the integration of U-Net as well as ResNet50, which made it simpler to accurately and efficiently draw the tumour's boundaries.

Sajid et al. created a hybrid CNN method for brain tumour identification using BRATS MR images [17]. This two-phase training approach as well as dropout were among the complicated regularization strategies whose effectiveness was examined and verified. When merging two- and three-path networks, their suggested hybrid model that improve the model's functionality. This model has performed well for various segmentation tasks with respect to the CNNs' capability analysis. Moreover, the training instances may result in better performance. Once the model is examined, it discovered 86% of Dice score, 91% of specificity, and 86% of sensitivity. Several kinds of MR images of brain tumours were gathered for this research work. Various machine learning algorithms were also considered to evaluate the efficiency of proposed CNN model. While comparing with TL models, the CNN performed better in this research. On the other hand, Haq et al., have demonstrated better outcomes with transfer learning models, achieving outcomes above 90% [18]. While considered this work and attempted to gain a complete understanding of this problem in the further research.

Furthermore, a model of this kind has been trained on a massive dataset (such as the ImageNet database), which has millions of pictures, transfer learning performs effectively in situations where the amount of data is restricted. For the purposes of the classification tasks, this method uses the pre-trained model with modified weights. Being limited to training the fully linked layers of the model, it also has the advantage of not requiring a large amount of processing power. Some transfer learning models might be applied to brain tumour diagnosis as a result of these advantages. Talo et al., employed a pre-trained ResNet34 framework to distinguish between images of abnormal and normal brain MRI data. High prediction accuracy is also achieved by extensive data augmentation [19].

Research Gap

Swati et al. have suggested a refined VGG19 model for the purpose of identifying multiclass brain tumours [20]. Subsequently, Lu e al., proposed an improved AlexNet architecture for the diagnosis of anomalies in the brain [21]. There were only 291 images utilized in this research. In a related work, Sajjad et al. performed multiclass brain tumour diagnosis on 121 pictures using an improved VGG19 model [22]. Prior to the augmentation of the data, their total prediction accuracy was 87.4%. The accuracy was eventually raised to 90.7% using the data augmentation approach. The challenges faced in previous research in improving the detection of brain tumor is addressed and focused to improve by introducing TL with CAE. This literature review assists in analyzing the novel method using TL as CAE with CNN-VGG19 method to improve the BT classification.

III RESEARCH METHODOLOGY

The BTs are intricate whereas the locations and the sizes of BT exhibit numerous anomalies. A qualified neurosurgeon is needed for MRI analysis, and countries that are developing, the shortage of qualified medical professionals and their ignorance of tumors result in it being extremely challenging and time-consuming to produce reports from MRIs. Hence, the automated system on cloud has ability in solving problem. This research focus on improving the classification accuracy for better detection of BT that can be done through the feature extraction method named CAE which is implemented with VGG19 with respect to CNN. The image dataset is fed into the CAE and the pre-trained CAE output has been utilized as the input for VGG19 based CNN. The CAE assist in considering the significant features from the available images as an input and the classification accuracy get accomplished. The overall architecture of predicting BT using CAE with VGG19 based CNN model. The architecture of predicting BT using CAE with VGG19 based CNN is shown in figure 1predicting BT using CAE with VGG19 based CNN model. The architecture of predicting BT using CAE with VGG19 based CNN is shown in figure 1.

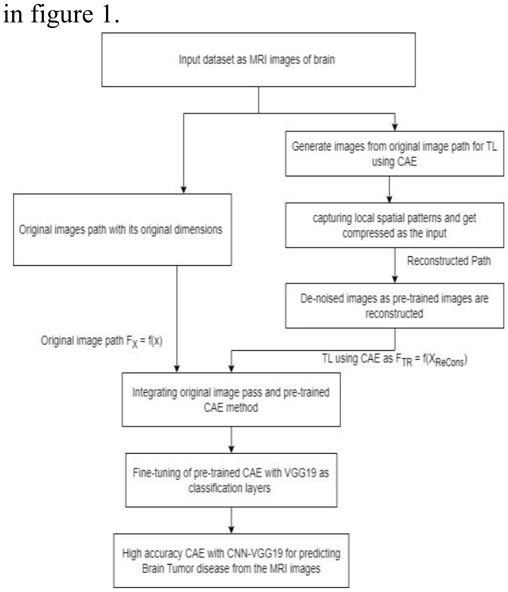

Figure 1 Architecture of predicting BT using CAE with CNN-VGG19

3.1 Data collection and Data preprocessing

Nearly 85% to 90% of patients affected with BT are majorly affected by Central Nervous System (CNS). For each year, 11700 people have been diagnosed by BT. Based on the 5-years survival rate, the individuals with CNS tumor is about34% for males and 36% for women. The BTs have been classified namely glioma Tumor, meningioma Tumor, Pituitary Tumor, and no tumor. Moreover, the exact treatment planning, and accurate diagnostics are implemented in improving the patient's life expectancy. Hence, the best examined by the radiologist. Image Data Generator is used for prepping training and validation data, including rescaling examined by the radiologist. Image Data Generator is used for prepping training and validation data, including rescaling.

In the case of validation data generator has 394 images with four classes. These are the two types of data generators. The rotation range produces a picture that is randomly rotated by up to 15 degrees, while the rescaling function helps with pixel value rescaling. The closest accessible pixel is utilized to fill in the missing pixels using the fill mode.

3.2 Working of CAE

The suggested CAE structure of architecture for image processing process with initial image as original image as shown in Figure 2. It represents the CAE output with compressed image of the utilized image datasets. The activation function with Rectified Linear Unit (ReLU) has placed with four batch layers of 2D convolutional as well as deconvolutional over symmetric architecture of the suggested CAE. The process that reverses the convolutional layer's function is called deconvolution, or transposed convolution. The input is specifically mapped from the space of low-dimensional to a high-dimensional.

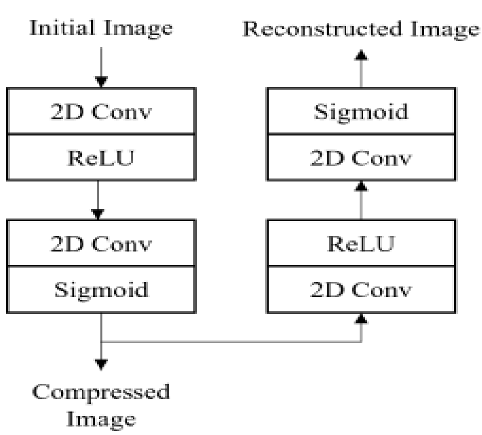

Figure 2 Topology of CAE

To be more precise, 2D Conv1-ReLU1 as the first layer has receives the input image with W × H × 3 dimensions. This procedure is referred to as the CAE Encoder's inputs as well as produces 32 down sample with mapping of spatial feature in dimensions as W/2 × H/2 using a size of 4 × 4 kernel and 32 filters. The 2D Conv2-ReLU2 as second layer have received the output from the encoder as well as utilized a size of 2 × 2 kernel with 3 filters to produce a compressed picture representation with dimensions of H/4 × W/4 × 3. It makes sense to use a kernel with a less size in the second layer as the output feature maps of the first layer have smaller dimensional sizes than the input image. Likewise, the opposite operation of the encoder is carried out symmetrically by the third layer as well as fourth layer as 2D Deconv3-ReLU3 and 2D Deconv4-ReLU4 respectively for the CAE decoder component.

3.3 Training using VGG19 based CNN

The Adam optimizer often enforces the ConvNet training process, with batch size set to 256, momentum up to 0.9, and 0 to 255. The penalty multiplier for sum of squared weight (L2) has been adjusted to 5x10-4 using weight regularization. Every vector requires a hyperparameter that must be set in Python using Keras to enhance the efficiency of an overfit DL network. The dropout ratio of 0.5 serves as the dropout regularization of to the first as well as second FC layers. On the other hand, the validation set's accuracy stops increasing when the learning rate is typically set at 0.01 and then subsequently decreased by a factor of 10. As a result, the learning rate is now three times lower and ends after 49 epochs of repetition. Consequently, it is guessed rather than having additional parameters and depth taken into account by CNN. Additionally, due of implicit regularization carried out by reduced convolution filter sizes and pre-initialization by particular layers, the network needed specific epochs to converge. In order to prevent gradient instability in deep networks during learning, poor initialization may contribute to the significance of the network weights. Adam optimizer, which initialized randomly in the training setup, was added to the configuration to prevent these problems. Five convolution layers and three FC layers are advanced in the VGG19 with CNN architecture. Consequently, the pre-initialized layer's learning rate is not decreased, which could permit modification throughout the learning process. The layer's random initialization sample setting advances the weight of the normal distribution with a mean of 0, a variance of 0.01, and an initial bias of 0.

3.4 Training process with VGG19 architecture

VGG19 layered method is mainly used in deep CNN for identifying the images with large scale. The RGB input source has been converted into the RBG images with size 224 x 224 as fixed. In general, the preprocessing VGG19 is executing by subtract the designed RGB mean value on the training dataset from each pixel. However, the BT input image have been made to be passed by convolution layers as well as max pooling layers stack whereas the filters are performed with 3 x 3 that isvery smaller in size for capturing the notation from center, up or down and left or right. Hence, it is efficient with 7 x 7 as the field of stacks with convolution layer and max pooling layer which has been utilized in VGG19 architecture. Once the input image passes through the non-linearity transformation, the 1x1 convolution filter has been used for linear transformation of input channel.

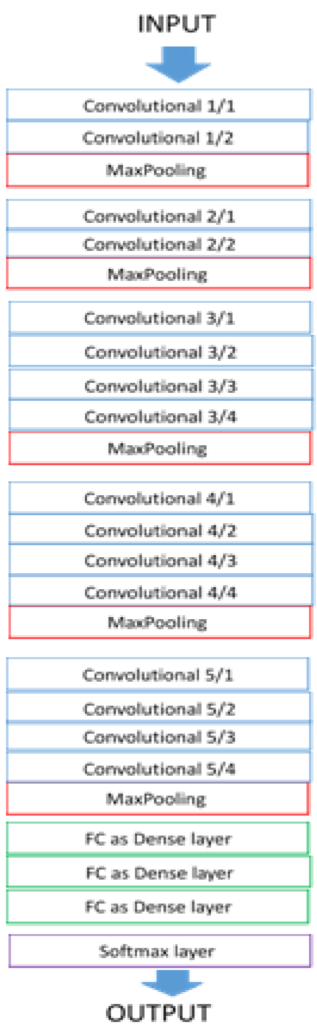

Figure 3 VGG19 architecture with CNN Mode

Moreover, the convolution stalk and the layer of convolution spatial padding as input has been fixed in single pixel with 3 x 4 convolution layers that determine the resolution of spatial is conserved once convolution is done. There are five numbers of max-pooling layers have been placed followed by the convolutional layers that assist in spatial pooling whereas the max-pooling get accomplished in a 2x2 window with stalk 2. There have been three layers of Fully-Connected (FC) followed by five different stacks of convolution and max pooling layer. The first two of FC layer consists of 1x1x4096 which illustrate that 4096 channels are available for each FC layer and the last FC layer with 1x1x1000 which perform 1000-way ILSVRC classification. Final layer has been deals with softmax layer shown in figure 3.

IV RESULTS AND DISCUSSION

For an experimental work, the high-performance server equipped with Intel Core i7, DMI2 CPU, 100GB of free space, 12GB RAM, and a Quadro K600 GPU was employed. Ubuntu 18.04.3 LST is the Operating System (OS) that was used to run the aforementioned GPU during the image dataset training process. The loss function and optimizer has been employed in proposed model with Adam and binary cross entropy. The VGG19 model basically pre-packaged with Keras which get imported from the module of keras applications. The constructor of the CNN-VGG19 model with CAE takes three primary arguments are

1. input_shape
2. weight
3. include_top

The network can process a wide range of input sizes thanks to the weight constructors which signifies the threshold weight from an initiated model like include_top, which involves a classifier with dense connections at the network top as well as input_shape represents the shapes of imagetensor. The usage of TL and CNN for detecting as well as classifying BT as an DL asset and for examining the tumor segmentation. Similarly, VGG19 model of CNN with CAEis weighted and evaluated. This study consists of 394 images involved with the size of 400x X 400x pixel and evaluation is done through two different metrics namely accuracy and loss. This research majorly focuses for involving VGG19 instead of considering hyperparameter with huge number and the VGG19 goal is to provide convolution layers with 3 x 4 filter using a three stalk with maxpooling each as well as frequent utilization of the similar padding to 2 x 2 convolution layer filter with maxpool every to two different stalks. This kind of arrangement has sequence with convolution layer monitored through one layer of max pool for every stalk frequently done by the whole architecture. Finally, it consists of 3 FC layers as dense layer subsequently a softmax for output. The VGG19 has involved with 19 layers consists of weights whereas VGG19 has VGG model variant that in short contain 19 layers such as 16-convolution layers, 5-MaxPool layers, 3-FC layers, as well as 1-SoftMax layer. Similarly, the 16 layers over VGG16 involves 16 layers through weights.

TABLE1 TRAINING AND TESTING IMAGES OF BT DATASET

BT dataset	Tumor Status	Image Count	Modelling Images	
			Training	Validating
BTimage	No Tumor	500	395	105
	Meningioma	937	822	115
	Glioma	926	826	100
	Pituitary	901	827	74

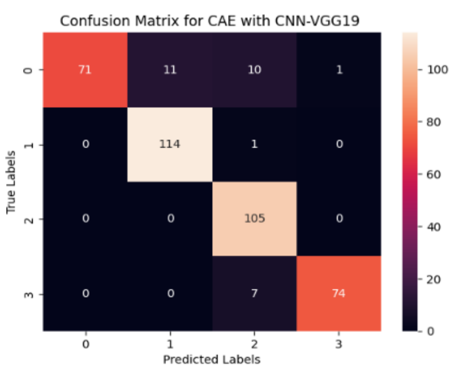

Figure 4 Confusion matrix heatmap for CAE with CNN-VGG19 method

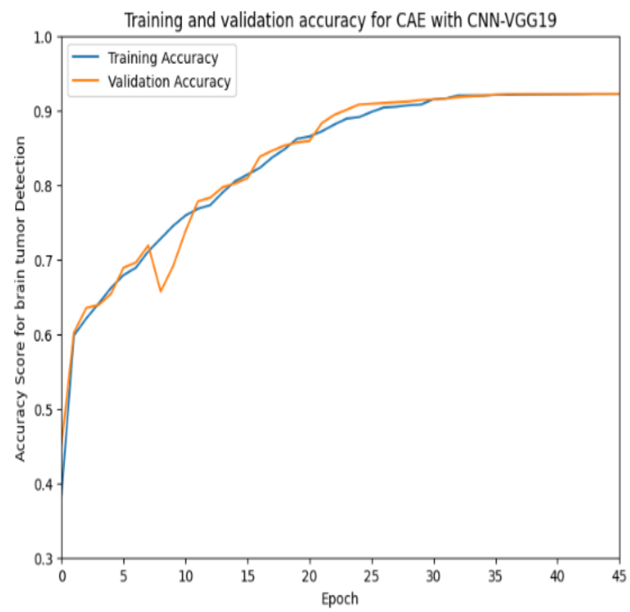

Figure 5 Accuracy curve for CAE with CNN-VGG19 method

Figure 4 illustrate the confusion matrix for CAE with CNN-VGG19 method which involved four different classes. The diagonal values are represented as True Positive (TP). The summation of each horizontal row value except TP is said to be False Positive (FP) for each class. The summation of each vertical column except TP is False Negative (FN) for each class. The brain tumor detection performance can be determined through model accuracy and model loss that has been initiated for training sample as well as testing sample shown in figures 5 and 6. The figure 6 has illustrated the model accuracy for train model and test model with 49 epochs as iteration of the CAE with CNN-VGG19 model. The accuracy for training begins from 38.4% and testing begins from 45.1% and as the epoch increase the accuracy became to increase in the training sample and get steady after 32 epochs that accomplish with 92.23%. In the case of testing, the accuracy increases gradually and sudden drop at 6^{th} epoch after it began to increase as epoch increases that finally accomplished with 92.39% as testing model accuracy. This assist to understand that CAE with CNN-VGG19 model has better recognition in detecting the brain tumor precisely. Figure 7 has illustrated the loss in training sample is from 0.616 to 0.079 and in the case of loss in testing sample is 0.549 to 0.071 which is lesser than training due to initializing the model hasn't learned better. When the epoch gets incremental and there is a reduction in loss from 0.616 to 0.079 which liable in determining that TL plays the role in minimizing the loss. According to validation loss, the loss value gets minimized from 0.549 to 0.071. Thus, the model has trained with the best method to classify the model with 92.39% accuracy.

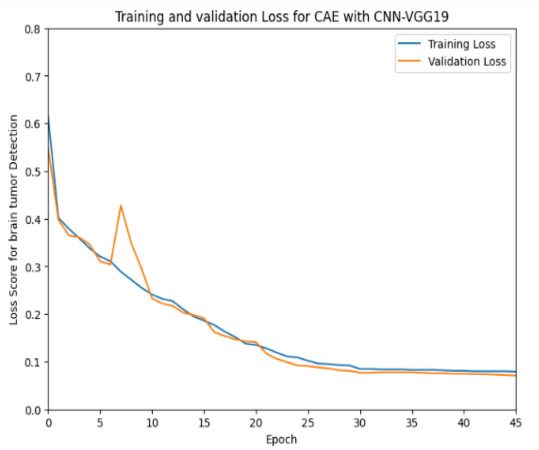

Figure 6 Loss curve for CAE with CNN-VGG19 method

TABLE 2 MODEL EVALUATION FOR VARIOUS CNN BASED CLASSIFICATION METHOD

CNN based Classification Method	Micro Precision	Micro Recall	Micro F1-Score	Weighted Precision	Weighted Recall	Weighted F1-Score
CAE with CNN-VGG19	92.39	92.39	92.39	93.26	92.39	92.22
CAE with CNN-VGG16	77.92	77.92	77.92	77.34	77.92	73.22

Table 2 illustrates the evaluation metrics to determine the proposed CAE with CNN-VGG19 has better accuracy while compared to CAE with CNN-VGG16 by Micro based and weighted based confusion matrix metrics.

Figure 7 illustrate the micro precision, micro recall and micro f1-score that determines the accuracy of the model. The model accuracy for CAE with CNN-VGG19 is 92.39% which is comparative higher than CAE with CNN-VGG16 is 77.92%.

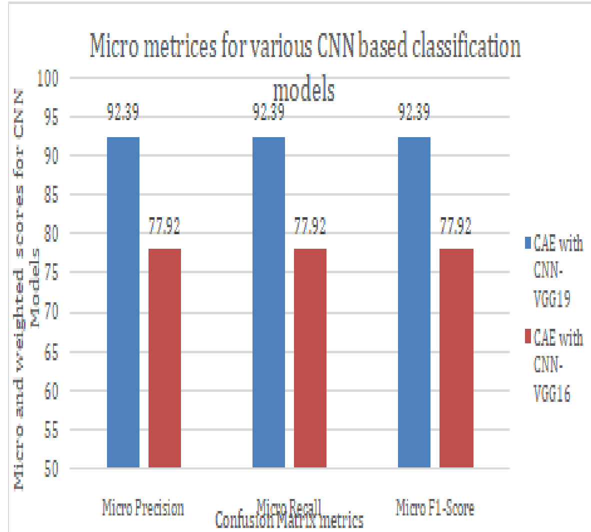

Figure 7 Micro Metrics Analysis

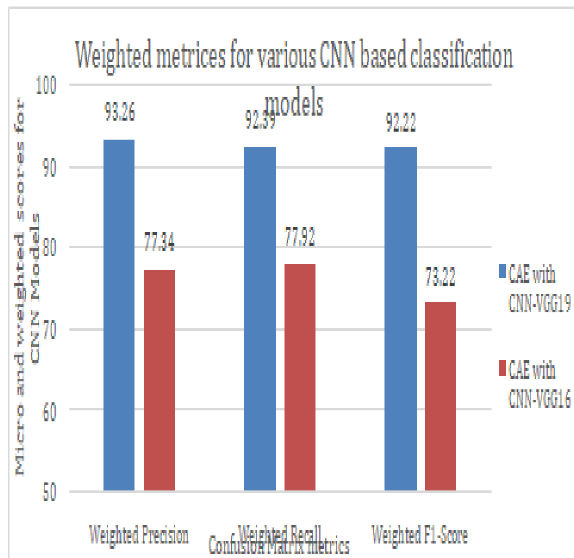

Figure 8 Weighted Metrics Analysis

Figure 8 illustrate the weighted precision, weighted recall and weighted f1-score that determines the TP rate and FP rate of the model. The model TP rate has been weighted through weighted recall of the model and similarly, FP rate has been weighted through weighted precision of the model. The CAE with CNN-VGG19 has high TP rate as 92.39% and FP rate as 93.26% which is comparative higher than CAE with CNN-VGG16 is 77.92% and 77.34%. Thus, the CAE with

CNNVGG19 has high accuracy in classifying the brain tumor precisely.

V CONCLUSION

To enhance CAE with CNN performance on the task of image classification, this proposed and suggested for the study to use CAE as a universal unsupervised learning data preparation technique for building robust as well as compressed representations of features. In image classification models, the used CNN models with VGG16 and VGG19 are typically taken into consideration. In this research, focused to determine that TL based method may lead to the highest performance CAE with CNN-VGG19 results compared with CAE with CNN-VGG19 models through model accuracy and model loss. Moreover, CAE with CNN-VGG19 model has evaluated with TP rate and FP rate in which the CAE with CNN-VGG19 method has ability to improve prediction accurately in detecting BT. Therefore, the prediction of BT detection is high accuracy in CAE with CNN-VGG19 using MRI. Thus, the CAE with CNN-VGG19 has better prediction in classifying the brain tumor precisely.

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