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Multiple Sclerosis Classification Using Deep Learning Techniques

Marwan Abo-zanona
Department of Management Information Systems
College of Business Administration
King Faisal University
Al-Ahsa 31982, Saudi Arabia
Email: mabozanoneh@kfu.edu.sa

Abstract— The diagnosis of Multiple sclerosis with different types is a big challenge for the doctor and takes more time in real life. We develop two deep learning techniques in order to classify the MS type. The MS has four types: MS-axial, control-axial, MS-sagittal, and control-sagittal. After that, we apply many preprocessing steps to the dataset in order to make it suitable to feed to the classification process like convert the target class label to numeric. We used four evaluation metrics to compare deep learning models: VGG19 and VGG16: recall, f1-score, accuracy, and precision. The results showed that the VGG19 gave better results compared with the VGG19 model in terms of four evaluation metrics of accuracy = 98.6%. The results indicated that we can rely on VGG19 in the classification process for many MS types.

Keywords- Multiple Sclerosis; Deep Learning; VGG16; VGG19;

I. INTRODUCTION *(HEADING 1)*

Multiple sclerosis (MS) is a chronic autoimmune condition that affects the central nervous system (CNS). It is characterized by inflammation leading to the destruction of myelin, the protective covering of nerve fibres, and the severing of axonal structures, as shown in Figure 1. These pathological changes are associated with irreparable neurological damage. MS is estimated to impact around 900,000 individuals residing in the United States [1]. MS is commonly identified in individuals between the ages of 20 and 30, primarily impacting several aspects such as physical capabilities, cognitive abilities, overall well-being, and occupational status. The etiology of MS remains uncertain; however, various genetic factors like the environmental factors like ambient ultraviolet (UV) radiation, vitamin D levels, tobacco smoking, and Epstein-Barr virus Type Style and Fonts.

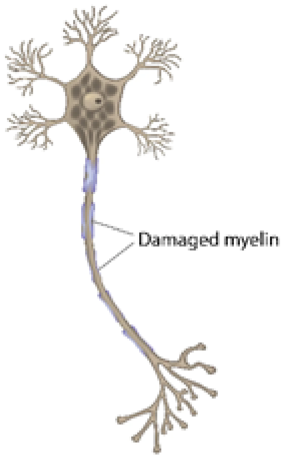

Figure 1. MS Disease.

The manifestation of symptoms associated with multiple sclerosis can vary among individuals. The symptoms may exhibit a fluctuating pattern or deteriorate progressively. MS has the potential to impact several regions of the central nervous system [3]. MS symptoms have been observed to exacerbate in response to elevated temperatures or concurrent infections, such as urinary tract or respiratory infections. The aforementioned symptoms encompass a range of manifestations, including visual impairments, challenges in maintaining equilibrium and mobility, cognitive impairment, sensations of numbness or weakness, particularly in the extremities, muscular rigidity, depressive symptoms, disruptions in sexual and urinary functions, as well as pronounced fatigue [1, 4].

MS has four clinical types: 1- Relapsing-remitting multiple sclerosis. 2- Secondary progressive multiple sclerosis [5]. 3- Primary progressive multiple sclerosis. 4- Clinically isolated syndrome. Individuals who have received a diagnosis of MS commonly undergo a series of diagnostic phases, a process that often evokes feelings of unease and fear [1, 6]. The MS management consists of several approaches like rehabilitation programs, disease-modifying therapies (DMTs), lifestyle modifications, symptomatic treatment, and psychological support. In 1993, the US Food and Drug Administration has approval for the first drug, called interferon beta-1b. in 2020, a total of nine classes of DMTs had received approval for the treatment of MS: cladribine, teriflunomide, glatiramer acetate, interferons, sphingosine 1-phosphate receptor modulators, fumarates, natalizumab, ocrelizumab, and alemtuzumab [1, 7]. This type of chronic autoimmune condition can be mitigated by developing artificial intelligence techniques including deep learning.

Nevertheless, the process of diagnosing MS by MRI or any type of medical imaging is characterized by its lengthy duration, exhausting nature, and vulnerability to human mistakes. Hence, artificial intelligence (AI) is employed to automate the diagnosis of MS through the utilization of deep learning (DL) and machine learning (ML) techniques [8]. ML is a subfield of AI that allow computers to improve and learn the performance without human interaction. DL is a specific field ML that use many algorithms to build tool by training with huge data through neural networks [8].

ML and DL have supported a lot of advantages in the medical field by allowing physicians to receive support in the following fields [9]: 1) disease prediction realm, which enables for timely notifications to be sent to them. 2) Promptly and precisely detecting the disease. This, in turn, enhances the quality of life for affected individuals [9]. Thirdly, the analysis of diverse blood, cerebrospinal fluid (CSF), and radiological markers can be utilized to predict the progression of the disease from a moderate form to another. Finally, it is important to consider the efficacy of specific medications in both preventing the progression of the disease and monitoring its treatment [9].

This paper aims to apply deep learning algorithms to predict and classify the MS type among four types. The techniques are convolutional neural networks, and VGG16. The reminder of this paper is structured as follows: Section 2 presents the previous papers that are related to this topic. Section 3 describes the proposed methodology used in terms of the dataset used, how we prepare the dataset, and the deep learning techniques. Section 4 explains the experimental results based on four evaluation metrics. Section 5 concludes the paper and suggests some future work.

II. Literature Review

Tousignant et al. [10] used deep learning system for the estimated of future patient impairment progression relied on the multi-modal brain Magnetic Resonance Images of patients with MS. The proposed model able to estimate the future illness progression reliably by conducted the experiments conducted on 465 patients who were enrolled in the placebo arms of the studies. using the dataset of the patients that was provided, they have achieved 0:66~0:055 as an AUC. However, the AUC rises to 0:701~0:027 when additional lesion label masks are supplied as inputs as well. Storelli et al. [11] evaluated a deep learning model with two expert physicians in order to predict worsening of the disease after two years of follow-up on a multicenter cohort of Multiple sclerosis patients obtained from the Italian Neuroimaging Network Initiative. Baseline and 2-year clinical and cognitive assessments, as well as T1-weighted brain MRI scans and baseline T2-weighted, were gathered from the Italian Neuroimaging Network Initiative repository for 373 MS patients. CNNs were used as the foundation for a deep learning architecture that was designed to predict either (1) clinical deteriorating, (2) cognitive degradation, or (3) both. Two expert physicians' performances were compared with the method's testing on a separate data set. The CNN model performed well in the test set in terms of cognitive (67.7%) and predicting clinical (83.3%) worsening; however, the best results were obtained when the algorithm was trained using both EDSS and SDMT data (85.7%). Two expert physicians' ability in classification was surpassed by artificial intelligence (70% accuracy for the human raters).

In order to improve the supervised machine learning system performance and categorize the disease's progression, Jannat et al. [12] provided an effective Multiple Sclerosis detection strategies. The existence of imbalanced data with a relatively tiny number of lesions pixels made MS lesion detection more difficult. Data from MS patients that collected from the Laboratory of Imaging Technologies is used to assess their pipeline. The FLAIR series, which stands for fluid-attenuated inversion recovery, is integrated to provide a faster system without sacrificing readability or accuracy. Convolutional neural networks are the foundation of our strategy. To train the model and categorize the disease progression, they employed SoftMax as an activation function and transfer learning. The results demonstrated the usefulness of MRI for MS lesions. Disease progression can be correctly predicted by analyzing brain MRIs of 100 healthy individuals and 30 sufferers. Clinical professionals must manually identify lesions, which is difficult and time-consuming because it requires analyzing a lot of MRI data. They demonstrated a noteworthy accuracy rate of up to 98.24% with their approach.

Montolío et al. [13] enhanced the diagnosis of MS and forecasted the extended duration of impairment in MS patients by utilizing clinical information and the thickness of the retinal nerve fiber layer, as determined by optical coherence tomography. 108 MS patients were enrolled, 82 of whom had a 10-year follow-up, and there were 104 healthy controls in total. Two predictive models, the MS diagnosis model and the MS disability course prediction model, were created by testing various classification algorithms, including long short-term memory (LSTM), decision trees (DT), multiple linear regression (MLR), Naïve Bayes (NB), ensemble classifier (EC), k-nearest neighbors (k-NN), and support vector machines (SVM). When it came to MS diagnosis, EC produced the greatest results (sensitivity: 87.0%, precision: 88.7%, accuracy: 87.7%, specificity: 88.5%, AUC: 0.8775). According to this impressive performance, the accuracy with k-NN was 85.4%, and with SVM, it was 84.4%. Additionally, the most suitable classifier for long-term MS impairment course prediction was the LSTM recurrent neural network (sensitivity: 81.1%; AUC: 0.8165; specificity: 82.2%; accuracy: 81.7%; precision: 78.9%). Utilizing SVM, MLR, and k-NN also demonstrated strong results (AUC $\geq$ 0.8).

An algorithm was developed by Roca et al. [14] that utilized various machine-learning approaches to forecast MS patients after two years, using just sex, fluid attenuated inversion recovery (FLAIR) MRI data, and age. Their algorithm integrated multiple predictors that complemented each other: a deep learning predictor based on a CNN. The predictors were aggregated using a weighted average, which considered prediction errors for various EDSS ranges. The training dataset contains 971 individuals diagnosed with MS. These individuals had undergone first FLAIR MRI scans and had corresponding EDSS scores recorded at the two-year mark. A test dataset consisting of 475 participants was given, although it did not include an EDSS score. A validation set of 10% of the training dataset was utilized. Their system successfully forecasted the EDSS score in patients diagnosed with MS, achieving a mean squared error (MSE) of 2.2 with the validation dataset and an MSE of 3 with the test dataset.

Roca et al. [15] introduced a profound machine learning technique to automatically classify cases of multiple sclerosis and its similar conditions. They then compared their model performance with that of two expert neuroradiologists. A retrospective collection of 268 brain magnetic resonance imaging scans, including both T2-weighted and T1-weighted scans, was obtained from patients diagnosed with 56, 70, 91, and 51 for migraine, multiple sclerosis, neuromyelitis optica spectrum disorders, and central nervous system vasculitis, respectively. The neural network model, utilized a cascade of 4 three-dimensional convolutional layers, followed by a fully connected layer for feature extraction. The automated system outperformed expert raters in terms of overall performance, with the most significant misdiagnosis occurring when distinguishing between neuromyelitis optica spectrum illnesses and vasculitis or migraine.

Coronado et al. [16] evaluated the efficacy of CNN in accurately segmenting gadolinium-enhancing lesions in a substantial group of patients with MS. They used the dataset that contains an MRI data from 1006 individuals with relapsing-remitting MS. The network's performance was assessed using three different combinations of multispectral MRI as input: T2-weighted, proton density-weighted, and pre- and post-contrast T1-weighted images; FLAIR; (U1) only post-contrast T1-weighted images; (U2) pre- and post-contrast T1-weighted images. The evaluation of segmentation performance was conducted using the true-positive (TPR), Dice similarity coefficient (DSC) and false-positive (FPR) rates on a lesion-wise basis. The evaluation of performance was also conducted based on the enhancement of lesion volume. The average DSC/TPR/FPR values for all improving lesion sizes were 0.77/0.90/0.23 when utilizing the U5 model. The results for the greatest augmentation volumes (>500 mm3) were 0.81, 0.97, and 0.04. The average values for DSC/TPR/FPR for U2 were 0.72/0.86/0.31. U1 demonstrated similar performance. The network's performance deteriorated as the enhancement size dropped, regardless of the input type.

TABLE I. SUMMARY OF PREVIOUS WORKS

Ref	Year	Algorithm	Dataset	Evaluation Metrics	Results
[10]	2019	Deep learning model	465 patients	AUC	AUC of 0:66~0:055
[11]	2022	CNN two expert physicians	373 MS patients	Accuracy	Accuracy of CNN is 85.7%
[12]	2021	CNN	Laboratory of Imaging Technologies dataset	accuracy rate	Accuracy = 98.24%
[13]	2021	MLR SVM DT k-NN NB EC LSTM	108 MS patients	Accuracy	Accuracy of EC: 87.7%
[14]	2020	- CNN - Random Forest Regressors - Manifold Learning Trained	971 individuals diagnosed with multiple sclerosis	MSE	MSE of CNN is 2.2
[15]	2021	- Deep learning - Two expert neuroradiologists	268 brain magnetic resonance imaging scans	Accuracy	Deep learning gave higher results
[16]	2021	CNN	1,006 MRI images	Dice similarity coefficient true-positive rate false-positive rate	The CNN gave the following results based on three metrics: 0.77/0.90/0.23

III. PROPOSED METHODOLOGY

Figure 2 presents the proposed methodology used in this paper to predict and distinguish between the disease's types of Multiple Sclerosis: Control-Sagittal, MS-Sagittal Control-Axial, and MS-Axial.

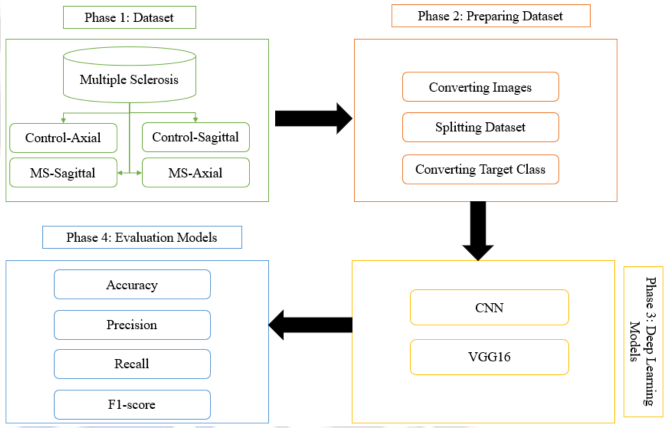

Figure 2. Proposed Methodology Architecture

A. Dataset Overview

In this study, we used the Multiple Sclerosis dataset that obtained from the Kaggle Website. This dataset contains 3,427 images in png format contains four types of Multiple Sclerosis: Control-Axial, Control-Sagittal, MS-Sagittal Control-Axial, and MS-Axial. Table 2 shows the count images in each type, and Figure 3 shows the example of the four types.

TABLE II. MULTIPLE SCLEROSIS DATASET FREQUENCY.

Type	Frequency
Control-Axial	1,014
Control-Sagittal	1.002
MS-Axial	650
MS-Sagittal	761
Total	3,427

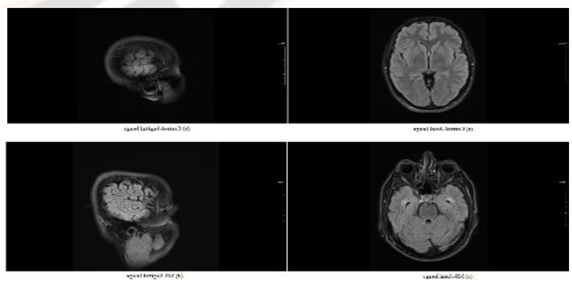

Figure 3. Examples form the MS Dataset.

B. Preparing Dataset

This step is crucial steps in the prediction process because of the dataset with image format need to apply many preprocessing steps before feed it in the deep learning techniques. In this paper, we applied three steps: convert the dataset form image format to

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the suitable format like arrays. Second, because the target class is four types of the MS, we need to transform each type to numeric value. Finally, the dataset must be divided into training and testing dataset. we build the model based on training dataset and we evaluate the performance of this model based on the testing dataset.

C. Deep Learning Algorithms

In this section, we present two deep Convolutional Neural Network (CNN) techniques used to accomplish the detection process effectively. These techniques are VGG16, and VGG19. CNN is a deep learning method specifically designed for efficient picture recognition and processing applications. The structure consists of several layers, which comprise pooling layers, convolutional layers, and fully linked layers. CNN function by extracting distinctive characteristics from images through the utilization of convolutional layers, pooling layers, and activation functions. CNNs utilize these layers to acquire intricate associations between features, detect objects or features irrespective of their location, and diminish the computational intricacy of the network.

VGG is an acronym for Visual Geometry Group. It is a widely used CNN architecture that consists of many layers. The term "deep" in the context of VGG-16 or VGG-19 alludes to the significant number of convolutional layers, specifically 16 and 19 layers respectively. The VGG architecture serves as the foundation for revolutionary models in object identification. Furthermore, it remains one of the most widely used image recognition frameworks at now.

- VGG16 Technique

VGG16 is a renowned CNN model that is widely regarded as one of the most exceptional computer vision models available presently that consists of 16 layers. The developers of this model assessed the networks and enhanced the depth by employing an architecture that utilized compact (3 x 3) convolution filters. This modification resulted in a notable enhancement compared to the previous configurations used in the field. Figure 4 shows the architecture of the VGG16 that used in detection process. During the training and testing process, as shown in Table 3, the values of the VGG16 parameters are shown as following: number of epochs is 50, loss function is categorical_crossentropy, metric used is accuracy, optimizer function is Adam with learning rate 0.001, and the batch size is 32.

TABLE III. HYPER PARAMETERS OF VGG16

Hyper Parameters	VGG16	
Convolution Layers	13	
Number of Neurons in convolution layers	First	64
	Second	64
	Third	128
	Fourth	128
	Fifth	256
	Sixth	256
	Seventh	256
	Eighth	512
	Ninth	512
	Tenth	512
	Eleventh	512
	Twelfth	512
	Thirteenth	512
Max Pooling Layers	5	
Fully Connected Layers	3	
Activation Function	Relu	Softmax
Train / Test Split	0.80	0.20
Kernal Window Size	(3,3)	
Pool Size	(3,3)	
Trainable Params	66,180	
Epoch	50	
Batch Size	32	
Optimizer	Adam	
Loss function	categorical_crossentropy	
Metric	Accuracy	

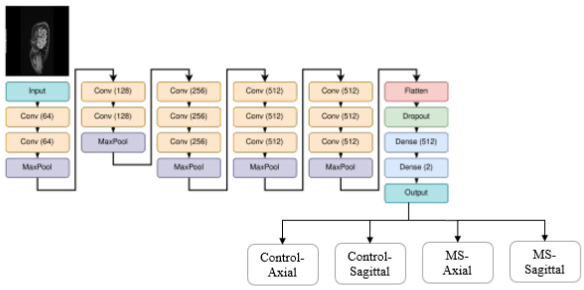

Figure 4. VGG16 Architecture.

- VGG19 Technique

The VGG19 model, sometimes known as VGGNet-19, is similar to the VGG16 model, with the only difference being that it consists of 19 layers instead of 16. The numbers "16" and "19" represent the quantity of weight layers in the model, specifically referring to the convolutional layers. Figure 5 shows the architecture of the VGG19 that used in detection process. During the training and testing process, as shown in Table 4, the values of the VGG19 parameters are shown as following: number of epochs is 50, loss function is categorical_crossentropy, metric used is accuracy, optimizer function is Adam with learning rate 0.001, and the batch size is 32.

TABLE IV. HYPER PARAMETERS OF VGG19

Hyper Parameters	VGG19	
Convolution Layers	16	
Number of Neurons in convolution layers	First	64
	Second	64
	Third	128
	Fourth	128
	Fifth	256
	Sixth	256
	Seventh	256
	Eighth	256
	Ninth	512
	Tenth	512
	Eleventh	512
	Twelfth	512
	Thirteenth	512
	Fourteenth	512

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	Fifteenth	512
	Sixteenth	512
Max Pooling Layers	5	
Fully Connected Layers	3	
Activation Function	Relu	Softmax
Train / Test Split	0.70	0.30
Kernal Window Size	(3,3)	
Pool Size	(3,3)	
Trainable Params	3,278,936	
Epoch	50	
Batch Size	32	
Optimizer	Adam	
Loss function	categorical_crossentropy	
Metric	Accuracy	

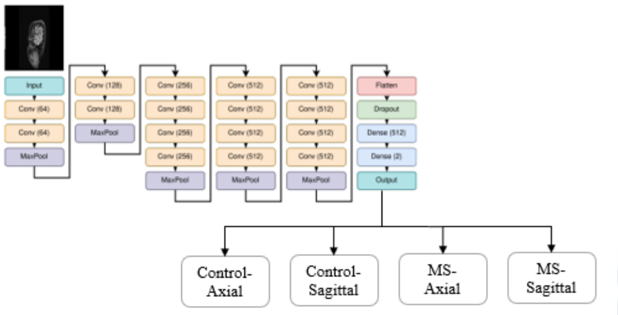

Figure 5. VGG19 Architecture

IV. Experimental Results

This section explained the experimental results that were produced after applied VGG19, and VGG16 techniques on the dataset. These results are based on four evaluation metrics used in classification task: precision, recall, accuracy, and f1-score. The formula and shallow explanation are shown below, where TP refers to True Positive, FN refers to False Negative, TN refers to True Negative and FP refers to False Positive:

- Accuracy: The most comprehensible performance metric is the ratio of accurately predicted samples to the total number of samples, or more simply, the ratio of accurately predicted samples to all samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- Precision: is determined by the ratio of correctly predicted positive samples to the total number of expected positive samples.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- The ratio of accurately anticipated positive samples to the total number of predicted positive samples is referred to as the Recall.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- F1-score: is the weighted average of Precision and Recall.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

We applied our experiments in this paper based on CNN and VGG16 techniques to predict the type of MS among four aforementioned types.

A. VGG19 Results

Figure 6 shows the performance results of the VGG19 after applied it to the dataset. the performance results of the VGG19 gave the higher results in prediction process as the following results: accuracy = 98.6%, precision = 98.6%, recall = 98.6%, and f1-score = 98.6%.

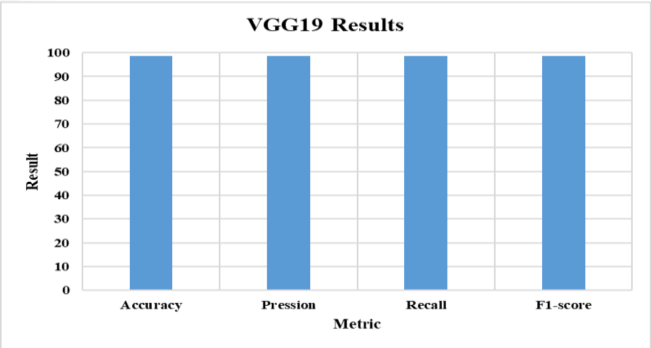

Figure 6. VGG19 Results.

As shown in Figure 7, we produce both training and testing accuracy for 50 epochs with batch size = 32.

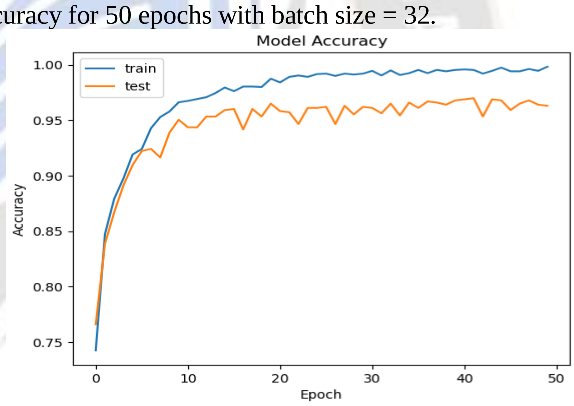

Figure 7. Training – Testing Results – VGG19

Figure 8 shows the confusion metric of the CNN, where there are four categories in this figure, where 0 = Control-Axial, 1 = Control-Sagittal, 2 = MS- Axial, and 3 = MS- Sagittal.

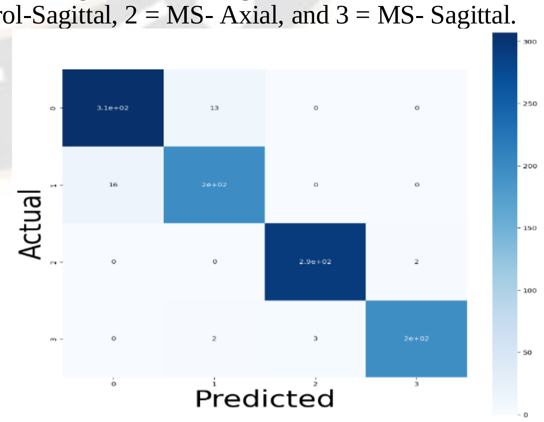

Figure 8. VGG19 Confusion Metric.

B. VGG16 Results

Figure 9 shows the performance results of the VGG16 after applied it to the dataset. the performance results of the CNN gave the higher results in prediction process as the following results: accuracy = 87%, precision = 87%, recall = 87%, and f1-score = 87%.

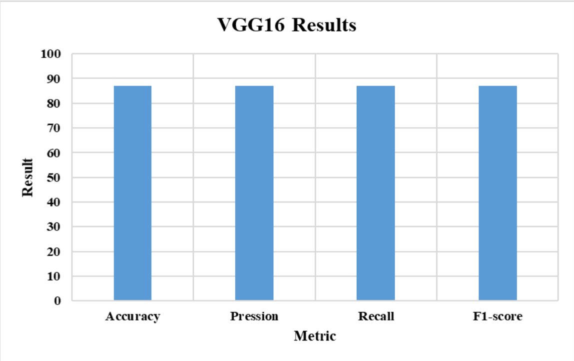

Figure 9. VGG16 Results.

As shown in Figure 10, we produce both training and testing accuracy for 50 epochs with batch size = 32.

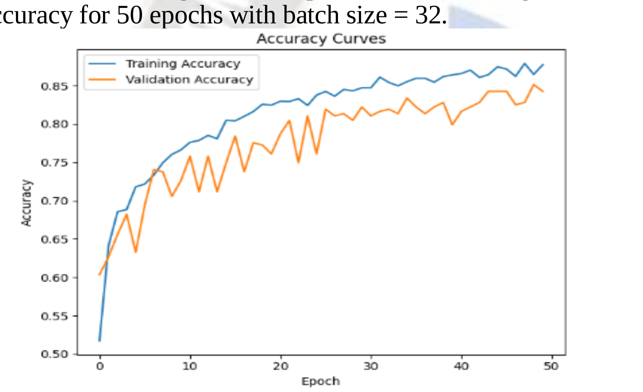

Figure 10. Training – Testing Results – VGG16

Figure 11 shows the confusion metric of the CNN, where there are four categories in this figure, where class 0 = Control-Axial, class 1 = Control-Sagittal, class 2 = MS- Axial, and class 3 = MS- Sagittal.

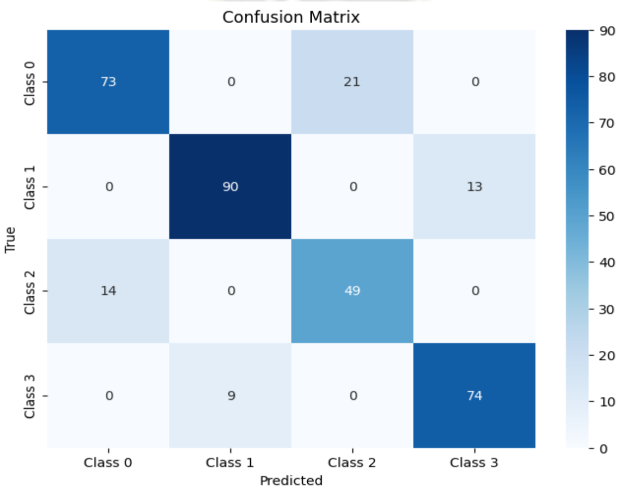

Figure 11. Vgg16 Confusion Metric.

The results obtained in this study outperform the previous papers that are summarized in the Literature Review section. For example, the author in [12] obtained an accuracy of 98.24% when using the VGG19 with different parameters. But we obtained 98.6 as an accuracy value in our study.

Finally, we can summarize the results for VGG16, and VGG19 in Table 3, and Figure 12.

TABLE V. PERFORMANCE RESULTS FOR CNN MODELS

Model	Accuracy	Precision	Recall	F1-score
VGG16	87	87	87	87
VGG19	98.6	98.6	98.6	98.6

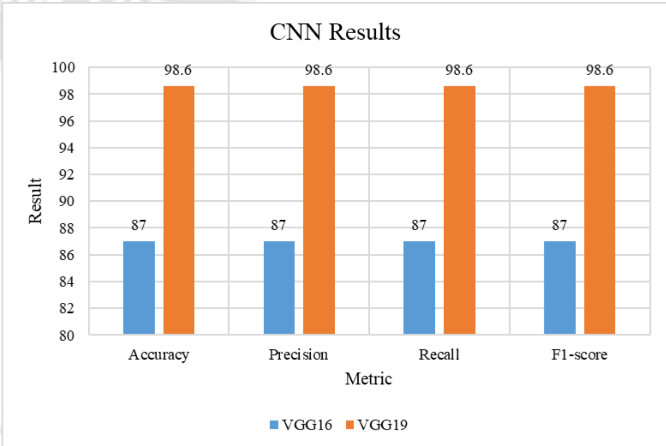

Figure 12. VGG16 and VGG19 Results.

V. CONCLUSION AND FUTURE WORK

This research presented the development of two deep learning approaches, namely the VGG19 and VGG16, for the purpose of classifying MS. Subsequently, we implemented numerous preprocessing techniques on the dataset to ensure its compatibility with the classification process. These techniques involved translating the data into a suitable format and transforming the target label from a categorical representation to a numerical one. Four assessment criteria, namely recall, f1-score, accuracy, and precision, were employed to compare the deep learning models VGG19 and VGG16. The findings indicated that the VGG19 outperformed the VGG16 model across four assessment metrics, achieving an accuracy rate of 98.6%. The findings suggested that VGG19 can be a dependable tool for classifying various kinds of MS. In our future work, we plan to conduct many experiments based on other deep learning or transfer models.

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