RESEARCH PAPER

Designing a Deep Learning-based Automated Multiple Sclerosis Detection Framework using Self-Channel Attention Diffusion Model

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Abstract-Multiple Sclerosis (MS) is an incurable disease that impacts the spinal cord and brain of the human body. When the system harms the protective cover of the nerves, this disease occurs and disrupts the transmission of signals in the body. Some of the common symptoms of MS include weakness of muscles, fatigue, memory issues, and vision issues. The MS illness may spread from one person to another, and so, early detection is essential, thus helping to manage the progression of the disease by slowing it. Thus, to offer early diagnosis, the work presents a new deep learning technique for the detection of MS. Initially, the required input images are collected from benchmark data resources. The gathered images are then directly applied to the classification network. MS detection is performed using the designed approach called the Self Channel Attention Diffusion Model (SCADM). This proposed model effectively learns complex, subtle patterns and performs accurate MS classification. Finally, the performance of the developed system is compared with existing models to validate its effectiveness. This approach offers significant potential for advancing intelligent healthcare systems and supporting early diagnosis of MS.

*Keywords-**Deep Learning; Automated Multiple Sclerosis Detection; Self Channel Attention Diffusion Model***

How to cite this article: Anilkumar P, Geetha C, Yogitha C, Meghana M, Pavani M, Bhavya K, Charitha C. Designing a Deep Learning-based Automated Multiple Sclerosis Detection Framework using Self-Channel Attention Diffusion Model. Int J Drug Deliv Technol. 2026;16(22s): 842-850. DOI: 10.25258/ijddt.16.22s.103

I. INTRODUCTION

MS, a long-term disease, greatly impacts the spinal cord and brain of the human body, where these are the two crucial organs that supports to form the central nervous system [1]. Generally, this disease arises when the immune system of the body wrongly assaults the protective covers of the nervous unit, which may result in severe damage, known as demyelination [2]. This demyelination paves the way to form the disease in the white and gray scale matters, leading to symptoms like weakness of the muscle, problems with clear vision, poor coordination, and complications with thinking and memory [3]. Nearly 2.8 million people suffer from MS throughout the world. There is no determination on the exact cause of this disease, but some researchers thought that it occurs owing to the combination of genetic features, problems that are inherent in the immune system and the environmental impacts, like low vitamin D and viral infections [4]. Since the prompt treatment aids in slowing the progression of the disease by increasing the life expectancy of people, early intervention is significant. But the diagnosis of MS is more challenging as it has no single testing tool to confirm the disease with complete confidence [5].

Magnetic Resonance Imaging (MRI) has become one of the useful and effective non-invasive tools, since it aids in detecting MS early [6]. MRI scans enable the researchers and the healthcare providers to notice the lesion region in the spinal cord and the brain, and also help them to monitor the disease progression over time [7]. Advanced MRI systems are effective in more accurately measuring the damages of the tissues [8]. Though the MRI scans are highly effective and sensitive, detecting and precisely outlining MS lesion areas is difficult. Thus, the manual segmentation through the medical experts can be considered as the best choice; however, it may be tiring, slower and can differ from one expert to another [9]. Moreover, it also makes the consistent detection even harder, as the lesions are generally larger in size and shape. Thus, it has the necessity to design an improved deep learning model, which aids in enhancing the detection process by automatically learning the significant trends and patterns that are present in the MRI scans [10].

The conventional clinical evaluation together with Magnetic Resonance Imaging (MRI) is still the gold standard in the evaluation of MS lesions, but owing to the heterogeneity of the disease and the subtle lesion characteristics, the conventional analysis of imaging studies is prone to inter-observer variability and lacks sensitivity in the detection of lesions [11]. Recently, deep learning and machine learning techniques have shown great potential in MS classification problems, utilizing large-scale MRI data to enable the automatic detection of the presence of disease, lesion distribution, and levels of severity. Convolutional Neural Networks and combined models have shown excellent classification accuracy, providing better sensitivity and specificity than traditional methods [12]. Systematic reviews and meta-analyses have confirmed that the analysis of MRI images using deep learning algorithms improves diagnostic efficacy significantly, with a combined classification accuracy of over 90%, which holds great promise for clinical applications [13]. Additionally, more recent architectures that utilize attention mechanisms, multi-scale feature extraction, and sophisticated preprocessing pipelines have also improved the ability to distinguish lesions and are less sensitive to imaging differences [14].

Depends on these significances, this work developed a novel system for MS detection leveraging the deep

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learning model, thus aiding in improving MS diagnosis and supporting clinical decision-making.

The subsequent points show the innovative contribution inherent in the developed MS detection system.

- To develop an intelligent end-to-end deep learning model for automatic and early detection of Multiple Scelerosis (MS) that directly extracts meaningful patterns from medical images without requiring manual feature engineering.
- To enhance the reliability, efficiency, and accuracy of MS detection by effectively handling demographic and image variations, thereby supporting informed clinical-decision making and improved patient care and disease management.
- To suggest the SCADM model for MS detection by integrating attention mechanism with diffusion enabled learning to progressively refine feature representations and capture subtle, disease specific patterns that baseline models may overlook.
- To enhance feature discrimination and robustness against image variations and noise through diffusion learning and attention-based selection of influential channel features, thereby improving automatic diagnosis and monitoring of disease progression.

The work's organization is given here. Section II briefly shows the literature works; Section III explains the background motivation and deep learning rationale for automated MS detection; Section IV describes the dataset characteristics and architectural overview of the proposed model; Section V details the development and novelty of the designed model for accurate MS detection; Section VI justifies the results and discussion, and Section VII concludes the work.

II. LITERATURE SURVEY

A. *Related Works*

In 2021, Zhang *et al.* [15] have interrogated 3 heatmap-generating techniques that had increasing generalizability for CNN interpretation: Class Activation Mapping (CAM), Gradient (Grad)-CAM, and Grad-CAM++. To investigate the impact of CNNs on heatmap generation, the model was also examined 6 different models trained to classify brain magnetic resonance imaging into 3 types: Relapsing-Remitting Multiple Sclerosis (RRMS), Secondary Progressive MS (SPMS), and control. Further, the novel method was designed to visualize and quantify the heatmaps to improve interpretability.

In 2025, Saeed *et al*. [16] proposed a novel hybridization of the multi-scale features extraction, multipathway 3D CNN, and Conditional Random Field (CRF) was employed for an automated MS lesion detection and segmentation. To capture regions of interest of various shapes and sizes, the multi-scale features was extracted using multi-resolution 3D input images for accurate MS lesion segmentation. To reduce over-segmentation, the CRF was employed as a post-processing step to refine the MS lesion segmentation by minimizing false positives. The CNN model was trained with 5 subjects with a mean of 4.4 time points taken from the ISBI 2015 MS lesion segmentation challenge. The results showed that the devised model obtained a total weighted score of 91.1%, which was higher than the human rater Score of 89.4%.

In 2025, Andishgar *et al.* [17] developed the R2AUNet DL model, incorporating recurrent residual blocks and attention gates within a 3D U-Net framework. The dataset included 112 MRI scans from 95 MS patients, collected between 2019 and 2023 at Shiraz Picture Archiving and Communication System (PACS). All patients had a confirmed MS diagnosis based on clinical assessments and the 2017 McDonald criteria, with manual lesion segmentations from expert neurologists as ground truth. The model was trained using an optimized preprocessing pipeline. Dice Similarity Coefficient (DSC), specificity, sensitivity, F1-score, and precision were used to evaluate performance.

In 2025, Umirzakova *et al.* [18] designed a CNN architecture specifically tailored for high-resolution T2-Weighted Imaging (T2WI), augmented by Deep Learning-based Reconstruction (DLR) techniques. The model incorporated dual attention mechanisms, including spatial and channel attention modules, to enhance feature extraction. A comprehensive preprocessing pipeline was employed, featuring bias field correction, skull stripping, image registration, and intensity normalization. The proposed framework was trained and validated on four publicly available datasets and evaluated using precision, sensitivity, specificity, and area under the curve (AUC) metrics.

In 2025, Haggag *et al.* [19] introduced a novel Content-Based Medical Image Retrieval (CBMIR) framework that leverages a newly designed Convolutional Autoencoder (CAE) model to improve the diagnostic evaluation of MS-related MRI scans. The proposed system extracts latent features from query and reference MRI images using the CAE. Extensive ablation studies involving nine distance metrics and diverse feature space dimensions identify 64 as the optimal latent feature size and validate the Mahalanobis distance as the superior similarity measure. Evaluated on four publicly available MS MRI datasets, the framework depicted good results demonstrating enhanced diagnostic accuracy. The system also outperformed existing similar CBMIR frameworks for other diseases in MAP scores and generalizes effectively without requiring extensive preprocessing or segmentation.

B. *Problem statement*

In recent years, MS has emerged as a critical neurological disorder that significantly impacts people across the globe. Early and accurate diagnosis of MS is essential for initiating timely treatment, slowing disease progression, and reducing long-term disability. However, conventional diagnostic practices rely heavily on manual interpretation of MRI scans and clinical assessments. To overcome these limitations, researchers have increasingly turned to automated systems. Despite their potential, these approaches encounter several key challenges:

- Many existing methods struggle to capture fine-grained lesion patterns and complex structural changes in the brain that are indicative of early-stage MS. Developing models capable of identifying these subtle neuroanatomical features is necessary.
- Current models demonstrate reduced efficiency when applied to large-scale MRI datasets and face implementation challenges due to their computational complexity. A lightweight and scalable solution is needed to ensure practical deployment in clinical environments.
- Although some deep learning models achieve high accuracy, they often fail to emphasize critical spatial and structural MRI features essential for MS detection. Incorporating attention mechanisms into the model architecture can enhance the ability to capture relevant lesion distributions and brain tissue abnormalities.

Therefore, this work proposes an efficient MS classification framework using advanced deep learning techniques to address these challenges. The proposed system aims to improve diagnostic accuracy, scalability, and interpretability. Table 1 outlines the limitations and strengths of existing MS detection models.

TABLE I. **LIMITATIONS AND STRENGTHS OF EXISTING MS DETECTION MODELS**

Author [citation]	**Methodology**	**Features**	**Challenges**
Zhang *et al.* [15]	Heatmap-based CNN	• Evaluated multiple visualization techniques to improve the interpretability of CNNs.	• Limited to comparison of heatmap methods without broader clinical validation.
Saeed *et al.* [16]	Multi-pathway 3D CNN with CRF	• Multi-scale feature extraction from 3D MRI inputs for accurate lesion segmentation. • CRF post-processing reduced false positives.	• Trained on a very small dataset, limiting robustness. • Performance may vary when applied to more diverse populations.
Andishgar *et al.* [17]	R2AUNet	• Integrated attention mechanisms to enhance lesion detection accuracy. • Used optimized preprocessing stage for better consistency.	• Achieved only a moderate dice score. • The dataset size is relatively small compared to broader clinical needs.
Umirzakova *et al.* [18]	CNN with DA and DLR	• Tailored for high-resolution T2-weighted imaging with spatial and channel attention. • The comprehensive preprocessing pipeline improved image quality and consistency.	• Requires high-quality imaging data, limiting use in resource-constrained settings. • Validation is restricted to four public datasets, not yet tested in clinical practice.
Haggag *et al.* [19]	CAE	• Extracted latent features and optimized similarity measures. • Achieved state-of-the-art MAP scores across multiple MS datasets.	• Focused on retrieval rather than direct lesion segmentation. • Limited exploration of integration with clinical workflows.

III. BACKGROUND, MOTIVATION AND DEEP LEARNING RATIONALE FOR AUTOMATED MULTIPLE SCLEROSIS DETECTION

A. ***Rationale for the Multiple Sclerosis Detection***

By creating mental issues and long-term physical problems, the occurrence of MS can affect the spinal cord and the brain of the human body. Early detection of MS is very crucial as it aids doctors to rapidly start the treatment by slowing down the disease progression. But diagnosing MS can be challenging because the presence of different signs and symptoms varies for each patient, and it is similar to some other neurological disorders. Generally, the doctors manually examine the MRI scans, but it requires more time and may results on difference in their opinions. The doctors may also overlook the unclear and small lesions present in the brain region throughout the visual monitoring. Due to these issues, it has a necessity to design an enhanced and automatic model to help doctors to identify MS disease in its initial stage and precisely. Such systems can support early diagnosis and improve patient care. Thus, recent models have applied deep learning for MS detection.

B. Significance of using a Deep Learning Model

In recent days, the use of deep learning models has become a supportive system for MS detection. By learning the complicated patterns automatically, these models are effective in offering accurate results. Most of the conventional approaches are based on manual features, while the deep learning systems aid in even analyzing the massive amount of data and detecting the subtle patterns that may be missed by human eyes. They can also minimize the reliance on expert interpretation and support to offer more optimal and resilient outcomes. Since the use of medical data continues to grow, the models based on deep learning have the ability to adapt to the performance on new and unseen datasets. Thus, this work also leverages the potential of such models to assist accurate, reliable and fast detection of MS disease, thus helping doctors to take better clinical decisions and boost patient outcomes.

IV. Dataset Characteristics and Architectural Overview of the Proposed Deep Learning Detection Model

A. Dataset Description

The section details the dataset explanation.

Dataset (**Brain MRI Dataset of Multiple Sclerosis with Consensus Manual Lesion Segmentation and Patient Meta Information**): The images are taken from https://data.mendeley.com/datasets/8bctsm8jz7/1. Access date: 2026-02-06. This dataset has a total of 180 records, where 135 are used for training (75%), while 45 are used for the model's testing (25%). Two image classes are involved in it, and they are normal with 43 images and MS with 137 images.

The collected images are indicated using the term MS_{Im}.

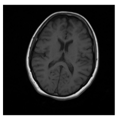
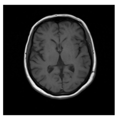
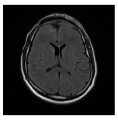
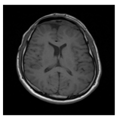
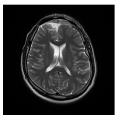
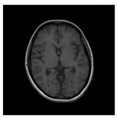
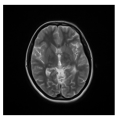
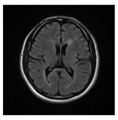
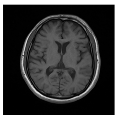
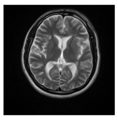
Images/ Classes	**1**	**2**	**3**	**4**	**5**
Normal					
MS					

Fig. 1. **Collected MS Sample Images**

B. *Architectural Overview of the Designed Model*

An innovative deep learning model is developed in this work to provide accurate detection of MS disease. It is effective in providing an automatic and reliable solution and also supports to make accurate decision for the given problem. By minimizing the assistance towards the manual intervention, the designed system helps to improve the diagnostic accuracy, resulting in reproducible and efficient results.

To begin the process, the necessary MRI images are garnered from the benchmark database, which aids in ensuring that the model can process using diverse features by capturing the variations that are present in imaging conditions and the patient demographics data. The, the images are directly fed to the SCADM model for the detection process. The existing models mostly depend on the handcrafted features; unlike them, the proposed SCADM system helps to process the collected images without the need for any pre-processing and feature extraction techniques. By the combination of diffusion-based learning and the channel attention networks, the recommended SCADM provides the optimal solution. Here, the channel attention allows the recommended system to concentrate only on the effective channel image features and the diffusion system aids in refining the learned representatives progressively by identifying the complicated and the subtle changes corresponding to the MS. The integration of such modules enables the recommended SCADM to accurately detect the diseased features that may be more challenging for standard imaging analysis. Fig. 2 provides the pictorial depiction of the designed MS detection model using deep learning.

C. *Development of SCADM*

The SCADM is designed as an enhanced framework, since it helps to improve the detection of MS. It also supports capturing the subtle and prominent disease patterns.

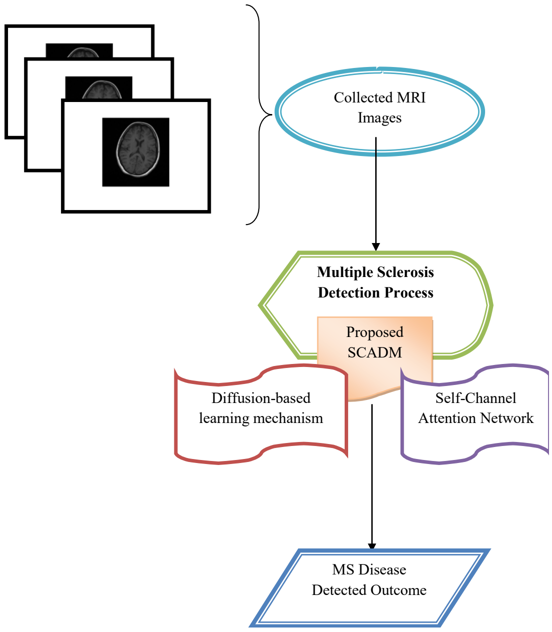


Fig. 2. **Pictorial Depiction of the Designed MS Detection Model using Deep LearningDevelopment Process and Novelty of Diffusion Model for Accurate Multiple Sclerosis Detection**

Working: The collected images MS_{Im} are initially given to the SCADM model to detect the MS disease by extracting the high and low-level features. The self-channel attention network used in this model aids in automatically identifying and emphasizing the most influential channel features by eliminating the unwanted ones, thus enhancing the quality of the images. This selective concentration towards the essential features enables the designed SCADM to provide early detection of the MS lesions.

In the self-attention module, the representation of the feature is a'_{w-1}, where it aids in fusing the global patterns that are created using the weight summation according to the value vector Y. Eq. (1) shows the mathematical view of this process.

$$a'_{w-1} - a_{w-1} + LN(Att(T,N,Y)) \quad (1)$$

Here, the query and key are T and N, while the term LN indicates the layer normalization unit, which helps to stabilize the process of training. Moreover, the attention is Att.

Finally, the obtained summed weight matrices are formulated using Eq. (2) to generate the optimal outcome.

$$Att(T,N,Y) = Soft\max\left(\frac{TN^{w}}{\sqrt{g_N}}\right)Y \quad (2)$$

Using the attention mechanism significantly enhances the capability of the designed system to model the complicated patterns.

Moreover, SCADM also used the diffusion-enabled learning mechanism, thus helping to refine the representation of the feature more deeply and progressively. This process, using the diffusion learning models, supports analyzing the complicated variations in the given images by reducing the noise that is inherent in the learned features.

In this, the step iterations are taken as w, where the noisy variables are forecasted according to the present data, indicated by a_w. The transitional detection outcome is a_{w-1}, where the probability of the conditional dispersion is given in Eq. (3).

$$s_\theta(a_{w-1} \mid a_w) = \Re\left(a_{w-1}; \mu_\theta(a_w, w), \Sigma_\theta(a_w, w)\right) \quad (3)$$

Here, the covariance and mean for the detection is $\Sigma_\theta(.)$ and μ_θ. Thus, the proposed model finally offered the MS disease detection outcome through the combination of diffusion and the attention mechanisms, thus helping to improve the feature discrimination, along with the model's robustness towards the outliers. The whole network is trained in an end-to-end manner employing the labeled database, helping with automated learning by eliminating the need for manual feature engineering. In this way, the recommended SCADM acts as an efficient and reliable framework to offer accurate MS classification and supports improved computer-aided diagnosis. Structural illustration of the SCADM-based MS detection model is given in Fig. 3.

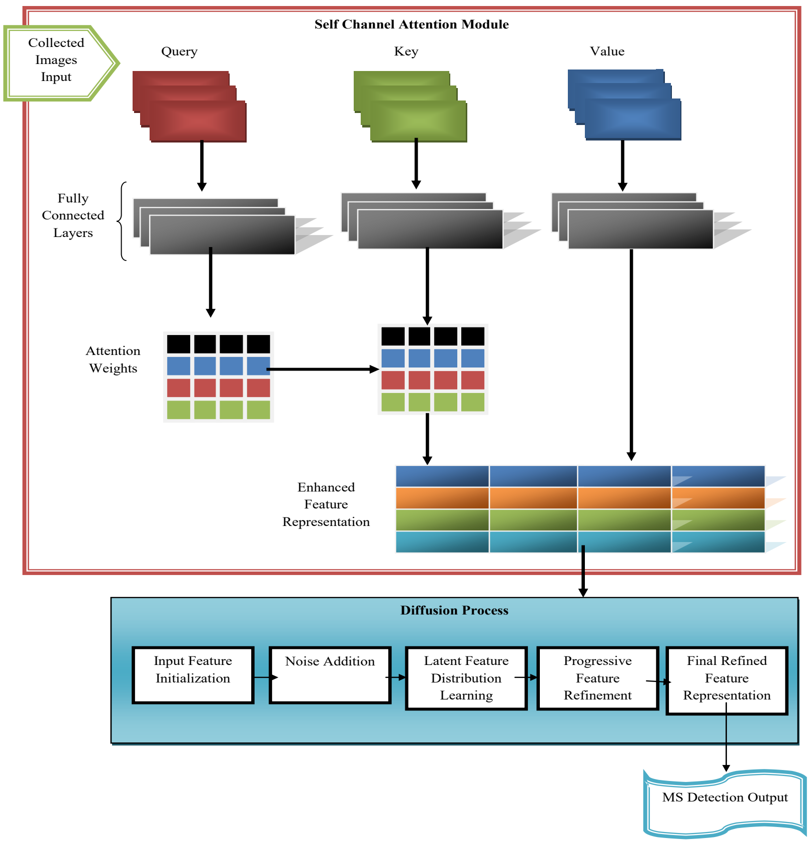


Fig. 3. **Structural Illustration of the SCADM-based MS Detection Model**

*D. **Novelty: SCADM for Multiple Sclerosis Detection***

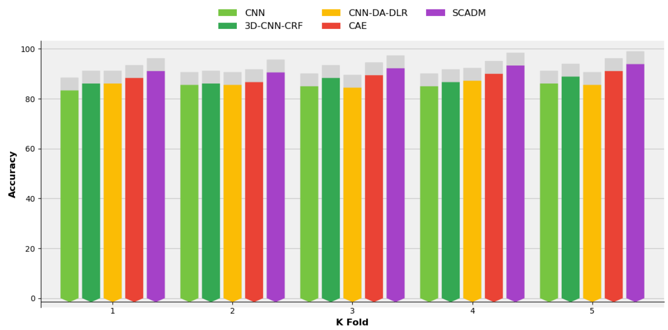
This work develops a novel model, named SCADM, to provide automatic detection of the MS disease. It combines the potential of diffusion-enabled feature learning with the attention network into a single system. The baseline models that are centered on deep learning equally treat all the channel features, but unlike them, the designed SCADM uses the self-channel attention element, which aids in prioritizing the most influential and effective channels based on the MS abnormalities. This targeted and innovative feature development allows the designed system to focus on the subtle lesion regions and the variation of tissues that may be missed by the conventional convolutional networks. Moreover, the integration of the diffusion mechanism has become another novelty incorporated in the proposed mechanism, which aids in refining the representations of the feature progressively by using the enhancement steps and the iterative denoising. This process further enhances the ability of the system to detect even the complicated information that is present inside the collected images. Moreover, by acting as the end-to-end solution, the SCADM helps to eliminate the requirement of handcrafted feature retrieval by minimizing the reliance on human intervention. Thus, the amalgamation of diffusion learning and the attention network makes the proposed system robust to the varied and noisy data. All these innovations comprehensively allow the SCADM to make it as a novel by attaining consistent, reliable and precise detection, representing a significant advancement over existing deep learning-based diagnostic approaches.

V. Results and Discussion

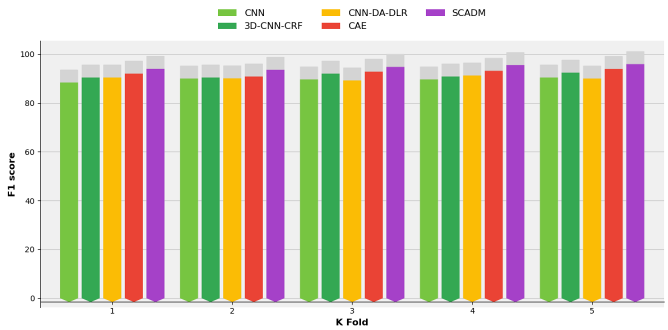
*A. **Simulation Setup***

Python was applied for the implementation. The model's performance was verified by comparing it with some of the conventional systems, like CNN [15], 3DCNN-CRF [16], CNN-DA-DLR [18] and CAE [19], respectively. The metrics used to check the performance of the proposed model are obtained using the link: https://en.wikipedia.org/wiki/Sensitivity_and_specificity.

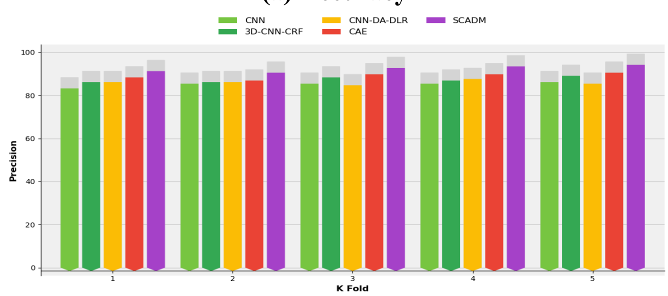
B. K-Fold Cross ValidationK-fold cross-validation of the proposed model is given in Fig. 4. Here, the models, like CNN, 3DCNN-CRF, CNN-DA-DLR and CAE, are used for the comparison with the proposed SCADM. Across the five folds, the proposed SCADM model achieves optimal results. When considering the accuracy in fold-1, CNN obtained 85%, 3D-CNN-CRF with 87%, CNN-DA-LR with 86%, CAE with 89%, and the proposed SCADM with 92%. In Fold 2, the values are close to CNN with 86%, 3D-CNN-CRF with 88%, CNN-DA-LR with 85%, CAE with 90%, and the developed SCADM with 93%. For Fold 3, performance slightly shifts with CNN with 87%, 3D-CNN-CRF with 89%, CNN-DA-LR with 84%, CAE with 91%, and developed SCADM with 94%. In Fold 4, the accuracies increase again, ranging from CNN with 88%, 3D-CNN-CRF with 90%, CNN-DA-LR with 87%, CAE with 92%, and SCAD with 95%. Finally, in Fold 5, the highest values are observed, with CNN with 90%, 3D-CNN-CRF with 91%, CNN-DA-LR with 86%, CAE with 93%, and the proposed SCADM with 96%. Thus, all these values proved that the developed model shows consistent performance towards the entire fold, indicating reliable and robust MS classification than existing approaches.



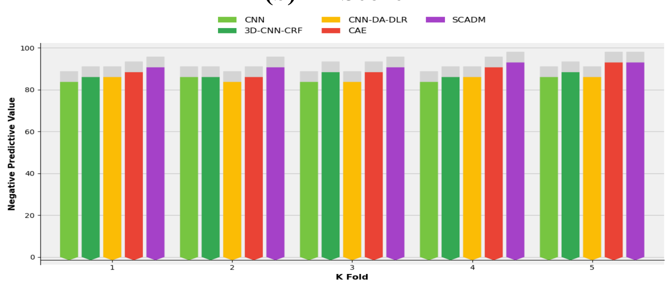
(a) Accuracy



(b) F1-Score



(c) Precision

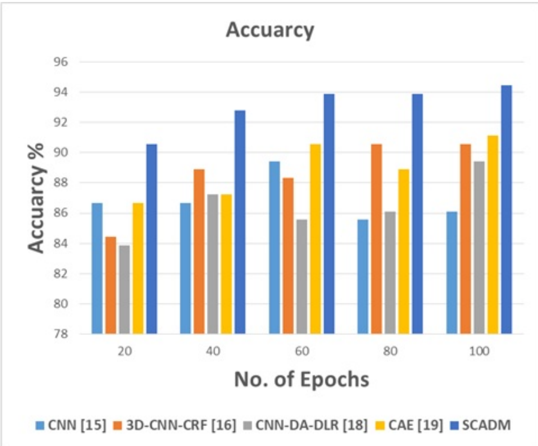


(d) Negative predicted value (NPV)

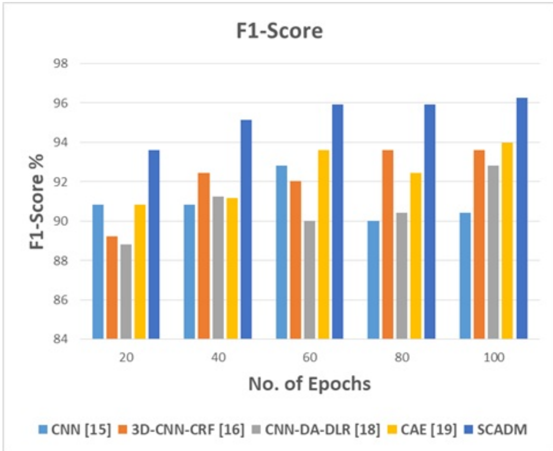
Fig. 4. **K-Fold Cross Validation on the Proposed Model in terms of (a) Accuracy, (b) F1-Score, (c) Precision, and (d) NPV**

*C. **Comparison Evaluation by Varying Steps Per Epochs***

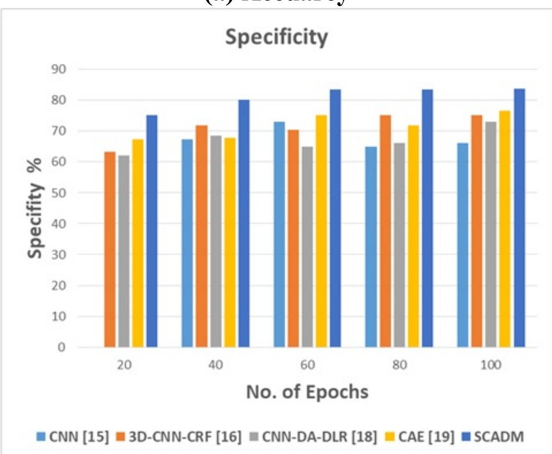
The quantitative performance comparison across different training steps is given in Table II. When the steps per epoch increase from 20 to 100, SCADM consistently achieves the highest accuracy, improving from 90.56% to 94.44%, while other models, such as 3D-CNN-CRF, CNN-DA-DLR, and CAE, provide lower performance. A similar trend is observed in specificity, where the developed SCADM attains 83.67% when considering the 100 steps, outperforming CNN with 66.07% and CNN-DA-DLR with 73.08%. The FPR decreases to 16.33% for the developed SCADM. Further, gives the lowest FNR of 1.53%, while based on the F1-score, SCADM achieves the highest value of 96.27%. Thus, these entire enhanced outcomes prove the inclusion of the diffusion model in the developed system, which aids in delivering reliable, clinically relevant and accurate detection to the MS disease.



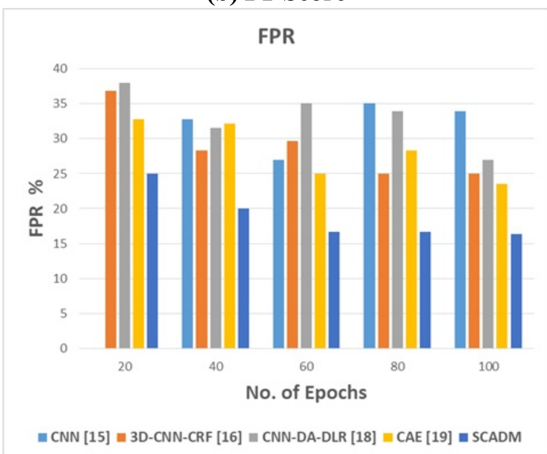
(a) Accuarcy



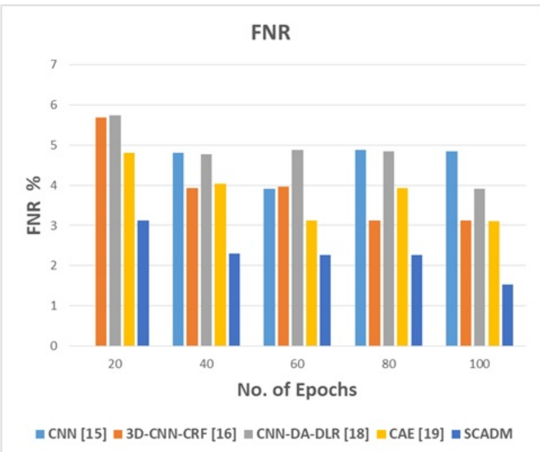
(b) F1-Score



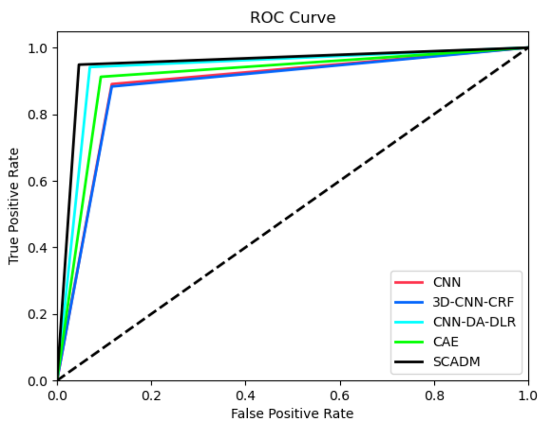
(c) Specificity



(d) False Positive Ratio



(e) False Negative Ratio



(f) ROC Curve

Fig. 5. **Performance evaluation of the Proposed Model in terms of (a) Accuracy, (b) F1-Score, (c) Specificity, (d) False Positive Ratio, (e) False Negative Ratio, and (f) ROC curve.**

TABLE II. COMPARISON EVALUATION BY VARYING STEPS PER EPOCHS

Steps per epoch	CNN [15]	3D-CNN-CRF [16]	CNN-DA-DLR [18]	CAE [19]	SCADM
Accuracy					
20	86.667	84.444	83.889	86.667	90.556
40	86.667	88.889	87.222	87.222	92.778
60	89.444	88.333	85.556	90.556	93.889
80	85.556	90.556	86.111	88.889	93.889
100	86.111	90.556	89.444	91.111	94.444
Specificity					
20	67.273	63.158	62.069	67.273	75.000
40	67.273	71.698	68.519	67.857	80.000
60	73.077	70.370	64.912	75.000	83.333
80	64.912	75.000	66.071	71.698	83.333
100	66.071	75.000	73.077	76.471	83.673
FPR					
20	32.727	36.842	37.931	32.727	25.000
40	32.727	28.302	31.481	32.143	20.000
60	26.923	29.630	35.088	25.000	16.667
80	35.088	25.000	33.929	28.302	16.667
100	33.929	25.000	26.923	23.529	16.327
FNR					
20	4.800	5.691	5.738	4.800	3.125
40	4.800	3.937	4.762	4.032	2.308
60	3.906	3.968	4.878	3.125	2.273
80	4.878	3.125	4.839	3.937	2.273
100	4.839	3.125	3.906	3.101	1.527
F1-Score					
20	90.840	89.231	88.803	90.840	93.585
40	90.840	92.424	91.255	91.188	95.131
60	92.830	92.015	90.000	93.585	95.911
80	90.000	93.585	90.421	92.424	95.911
100	90.421	93.585	92.830	93.985	96.269

VI. CONCLSUION

This work developed an automatic MS detection model using deep learning. For the detection, the deep learning model, named SCADM, is used. It was effective in tackling the limitations, like noisy data and subtle lesion variations, which are common things present in MRI data. SCADM helped to enhance the learning ability of the discriminative features, while enhancing the detection accuracy through the combination of the diffusion model with the self-channel attention system. Comprehensive experimental validations were carried out with the traditional systems, namely CNN, 3D-CNN-CRF, CNN-DA-DLR, and CAE, using several measures. At 100 steps per epoch, the proposed SCADM model achieves 94.444% accuracy, specificity reaches 83.673%, FPR is reduced to 16.327%, FNR drops further to 1.527%, and the F1-score of 96.269%. Thus, the proposed framework provides an efficient solution to offer intelligent MS detection for real-world medical imaging applications. Although the developed model is effective, it has some issues. The model's performance could be influenced by differences in MRI quality. Thus, the future research will focus on including lesion segmentation with multi-modal data to reduce model complexity.

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