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Multiple Sclerosis Severity Classification in MRI using SCAN-ExOrU-Net and Siren-CNN

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ABSTRACT

Multiple Sclerosis (MS) is a progressive neurological disorder that leads to significant structural and functional changes in the brain, impacting both white and gray matter. Magnetic Resonance Imaging (MRI) plays a critical role in MS diagnosis and monitoring, yet existing lesion-based classification methods often fail to capture broader pathological changes beyond visible lesions. This research proposes an advanced severity classification framework leveraging multimodal MRI data (T1, T2, and FLAIR) and integrating both lesion-specific and non-lesion-specific attributes. The proposed approach employs a novel Spatial-Channel Attention Networks Exponential Orthogonal U-Net (SCAN-ExOrU-Net) for precise lesion segmentation and Siren-CNN for severity classification. Additionally, a Multiscale K-Co-occurrence Clustering (MK-CoC) method is introduced for tissue grouping, while Dynamic Causal Modeling (DCM) generates connectivity matrices to analyze brain network alterations. Feature extraction combines morphological, textural, and connectivity-based attributes, and severity classification is enhanced using Dynamic Fuzzy Log Rule Prioritized Logic (DFLRPL). Experimental validation using publicly available MRI datasets demonstrates the proposed framework's superior accuracy in classifying MS severity compared to existing methodologies. This research provides a comprehensive and robust MS severity assessment model, potentially improving clinical decision-making and patient management.

Keywords: MRI, SCAN-ExOrU-Net, Siren-CNN

I. INTRODUCTION AND RELATED WORKS

Multiple Sclerosis (MS) is one of the progressive central nervous system diseases, which causes morphological and structural changes to the brain. It is characterized by unpredictable episodes of clinical relapses and remissions, followed by continuous progression of disability over time. The inflammatory and demyelinating process in MS causes multi-focal lesions and widespread atrophy in white and gray matter, often leading to physical disability, cognitive dysfunction, and unemployment. Magnetic Resonance Imaging (MRI) is crucial in supporting the diagnosis, monitoring the dynamics of the disease, and evaluating responses to treatments. Researchers have applied machine-learning algorithms to MRI datasets to analyze various MS conditions. Various segmentation and detection algorithms have also been proposed for MS lesion detection and classification from MRI using various image processing and analysis methods. These algorithms have been developed based on using a single MRI modality as well as using multiple MRI modalities, such as T1-weighted (T1w), fluid-attenuated inversion recovery (FLAIR), and T2-weighted (T2w). Single-modal methods are useful to segment the brain into base regions, such as white matter (WM), grey matter (GM), and CSF. In contrast, multi-modal methods have been preferred for more robust lesion detection. Various Deep Learning (DL) and Machine Learning (ML) models were developed to provide a fast and accurate detection of MS lesions in MRI. Some of the used ML and DL algorithms were Random Forest (RF), Support vector Machine (SVM), K-Nearest neighbor (KNN), Deep neural Network (DNN), Convolution Neural Network (CNN), and U-Net. However, the broader structural and functional integrity of the brain, such as gray matter, white matter, brain connectivity, and cerebrospinal fluid affected by MS was not well studied in the prevailing research works. Therefore, to provide better insights, this proposal uses SCAN-ExOrU-Net and Siren-CNN-based MS severity classification with the consideration of non-lesion-specific attributes.

Several studies have explored the use of machine learning and deep learning techniques for Multiple Sclerosis (MS) detection and classification based on MRI scans. These studies have primarily focused on lesion segmentation, severity classification, and the prediction of clinical disability. A summary of key contributions is presented below.

Zhang et al. (2022) proposed a data imbalance-aware deep neural network to identify chronic active MS lesions. Their model achieved a mean square error of 0.98, effectively addressing the issue of class imbalance. However, segmenting small and irregularly shaped lesions remained a challenge.

Lou et al. (2021) developed a method for detecting paramagnetic rims in MS lesions using the Synthetic Minority Oversampling Technique (SMOTE) in combination with a Random Forest (RF) classifier. Their approach classified lesions with an Area Under the Curve (AUC) of 0.82 and significantly reduced the need for manual intervention. However, the method required increased computational time, limiting its efficiency in real-time applications.

McKinley et al. (2020) introduced a Convolutional Neural Network (CNN)-based model to automatically detect lesion load changes in MS patients. Their study achieved an AUC of 0.71 and effectively reduced errors in lesion identification. However, identifying subtle, clinically relevant features remained a complex task, affecting the model's reliability in certain case.

Roca et al. (2020) used FLAIR MRI data with CNN models to predict clinical disability in MS patients. Their approach achieved high accuracy in early-stage disability prediction. However, factors such as motion artifacts, scanner resolution, and signal-to-noise ratio affected the reliability of their results.

La Rosa et al. (2020) developed a 3D U-Net model for cortical and white matter (WM) lesion segmentation in 3T MRI scans. Their approach attained a detection rate of 76%, ensuring accurate lesion segmentation. However, the model's performance was highly dependent on the quality of input MRI data, making it less robust to variations in imaging conditions.

These studies provide valuable insights into MS detection and classification. However, they primarily focus on lesion-based attributes, overlooking non-lesion-specific indicators such as gray matter atrophy, brain connectivity alterations, and cerebrospinal fluid changes. Our proposed approach addresses these limitations by integrating multimodal MRI data and employing advanced deep learning architectures for comprehensive MS severity classification.

The previously reviewed research on MS lesion detection and segmentation highlights several critical gaps and challenges. Most studies primarily focus on lesion-based attributes, overlooking the broader structural and functional integrity of the brain, including gray matter, white matter, brain connectivity, and cerebrospinal fluid, which are crucial for understanding the full scope of MS pathology. Accurate segmentation of MS lesions in T1, T2, and FLAIR images remains a challenge, particularly in cases where lesions are small, irregularly shaped, or located in complex anatomical regions, as observed in Zhang et al. (2022). Additionally, the quality of MRI scans can be compromised by factors such as motion artifacts, scanner resolution, and signal-to-noise ratio, leading to classification errors, as noted in Roca et al. (2020). Furthermore, most existing research relies on the Expanded Disability Status Scale (EDSS) for severity grading, which may not be sufficient for real-time MS diagnosis, as it lacks comprehensive feature-based severity classification. Another significant challenge is the identification of subtle, clinically relevant features that correlate with disability progression, a complexity observed in McKinley et al. (2020). Addressing these limitations requires a more holistic approach that integrates lesion-specific and non-lesion-specific indicators with advanced deep learning techniques for improved MS severity classification.

The proposed lesion and non-lesion-specific multiple sclerosis severity classification system, based on T1, T2, and FLAIR MRI images using SCAN-ExOrU-Net and Siren-CNN, aims to enhance accuracy and reliability in MS diagnosis. To classify MS severity levels, both lesion-specific and non-lesion-specific regions are analyzed using Multiscale K-Co-occurrence Clustering (MK-CoC) and Dynamic Causal Modeling (DCM) for tissue grouping and connectivity matrix generation. Accurate segmentation of small, irregularly shaped lesions in complex anatomical

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regions is achieved through the Spatial-Channel Attention Networks Exponential Orthogonal U-Net (SCAN-ExOrU-Net). MRI scan quality is improved using Adaptive Patch Non-Local Means Similarity (APN-LMS) and Min-Max Scaling (MMS) techniques. Additionally, severity levels are labeled using Dynamic Fuzzy Log Rule Prioritized Logic (DFLRPL), which processes multi-modal extracted features for precise classification. Finally, to identify subtle and clinically relevant features that correlate with disability progression, Mutual Information (MI)-based feature correlation is performed, ensuring a comprehensive and robust MS severity classification framework.

II. PROPOSED SYSTEM

The proposed system is designed for classifying the severity of Multiple Sclerosis (MS) based on multi-modal data, including MRI images and clinical information. It consists of several key steps, starting from data collection and preprocessing to feature extraction, feature fusion, severity labeling, and final classification. The system integrates advanced machine learning and deep learning techniques to ensure accurate severity assessment.

Data Collection

The dataset used in this study is obtained from Mendeley sources, consisting of T1-weighted (T1), T2-weighted (T2), and Fluid-Attenuated Inversion Recovery (FLAIR) MRI images. These images are essential for detecting MS lesions and assessing brain abnormalities. Along with MRI scans, the dataset includes clinical data and lesion segmentation masks that provide crucial information for MS severity classification.

Preprocessing

Preprocessing is a crucial step to enhance image quality and standardize the data before feature extraction. Several operations are performed during this stage:

Resampling: Ensures uniform voxel sizes across MRI images, which is necessary for accurate comparison and processing.

Noise Reduction: Applied using the Adaptive Patch Similarity Non-Local Means (APN-LMS) filtering technique. Unlike traditional Non-Local Means (NLM) filtering, which averages similar patches, APN-LMS dynamically adapts to the structural characteristics of the image by considering edge orientation and local textures. This approach helps preserve anatomical structures while effectively reducing noise.

Intensity Normalization: The Min-Max Scaling (MMS) technique is used to scale intensity values within a specific range, such as [0,1]. This enhances image contrast and ensures consistency across different MRI scans.

For clinical data, preprocessing includes handling missing values to ensure the integrity of the dataset before numerical conversion.

Numeralization

Since clinical data often includes categorical attributes such as patient history, symptom severity, and other medical parameters, these values need to be converted into numerical form for machine learning algorithms. One-Hot Encoding (OHE) is used to transform categorical data into binary vectors, allowing models to process them efficiently.

Tissue Grouping

After preprocessing, different brain tissues, including White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF), are grouped using an advanced clustering technique called Multiscale K-Co-occurrence Clustering (MK-CoC).K-Means Clustering (KMC) is a traditional approach used for segmenting tissues based on intensity values. However, it struggles to capture spatial relationships and textural differences in complex brain structures.To overcome this limitation, Multiscale Co-occurrence Matrices are introduced, which construct co-occurrence matrices at multiple scales. This approach captures both fine and coarse texture patterns in MRI images, improving tissue differentiation.

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Lesion Segmentation

Identifying MS lesions is a critical step in assessing disease severity. For this, the SCAN-ExOrU-Net model is used, which is an improved version of U-Net designed for precise lesion segmentation.U-Net is a popular deep learning architecture for medical image segmentation, known for its ability to capture fine details through skip connections.Exponential Orthogonal (ExOr) Initialization is introduced to fine-tune U-Net's hyperparameters, enhancing stability and reducing sensitivity to learning rate variations.Spatial-Channel Attention Networks (SCAN) are employed to improve segmentation accuracy by generating a weighted feature map. This attention mechanism enables the model to focus on critical regions where MS lesions are present.

Boundary Refinement

To further enhance the accuracy of lesion segmentation, morphological operations like dilation and erosion are applied.Dilation helps expand the lesion boundaries slightly to fill in small gaps or holes.Erosion refines the segmented boundaries, ensuring better delineation of lesion regions.These operations help produce a cleaner and more accurate lesion map for severity classification.

3D Volume Analysis

Once lesions are segmented, 3D volume analysis is performed to extract volumetric features. This step is crucial because the size, shape, and distribution of lesions provide important information about the severity of MS.

Time Series Extraction and Connectivity Matrix Generation

Beyond volumetric analysis, the system examines brain connectivity patterns.Time series extraction involves tracking how brain regions interact over time using MRI sequences.Dynamic Causal Modeling (DCM) is applied to generate a connectivity matrix, which captures direct and indirect interactions between different brain regions. This helps in understanding complex neural network disruptions caused by MS.

Feature Extraction and Fusion

The system extracts a comprehensive set of features from both MRI images and clinical data.These features are given next.Statistical Features: Mean, median, variance of pixel intensities.Texture-Based Features: Gray-Level Co-occurrence Matrix (GLCM) metrics like contrast, homogeneity, energy, and correlation.Shape and Volume Features: Volume, surface area, compactness, elongation, and eccentricity.Connectivity Features: Node degree, clustering coefficient, betweenness centrality, characteristic path length, and edge weight from DCM-based connectivity matrices.The extracted image and clinical features are then fused to create a robust feature set for severity assessment.

Severity Labeling

To assign severity levels (mild, moderate, severe, very severe), Dynamic Fuzzy Log Rule Prioritization Learning (DFLRPL) is introduced.Fuzzy Logic (FL) is useful for handling ambiguous or overlapping severity levels.However, traditional FL models struggle with scalability as the number of rules increases.Dynamic Log Rule Prioritization optimizes rule evaluation by focusing on the most relevant rules, reducing computational complexity while maintaining high accuracy.

Data Augmentation

The dataset may suffer from an imbalance where certain severity levels are underrepresented. To address this, Adaptive Synthetic Sampling Approach for Imbalanced Learning (ADASYN) is used to generate synthetic samples, ensuring a well-balanced dataset for training.

Feature Correlation

To enhance classification performance, the most relevant features are selected using Mutual Information (MI).MI measures both linear and non-linear dependencies between features.It ensures that only the most meaningful and non-redundant features are passed to the classifier, improving efficiency and accuracy.

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Severity Classification

The final step involves training a deep learning model for severity classification.Siren-CNN (Sinusoidal Representation Networks with Convolutional Neural Networks) is used.While traditional CNNs capture spatial patterns effectively, their activation functions may struggle with complex data relationships.Siren Activation Function replaces traditional activations with sinusoidal functions, enabling the model to capture high-frequency variations smoothly.This prevents issues like vanishing gradients and allows for better learning, especially in cases with intricate MRI textures.The proposed system integrates advanced preprocessing, segmentation, feature extraction, and deep learning techniques to classify MS severity accurately. By combining MRI-based volumetric analysis, brain connectivity modeling, and clinical data fusion, the system offers a comprehensive approach to MS assessment. The overall workflow is depicted in Figure 1, illustrating the step-by-step process from data collection to final severity classification.

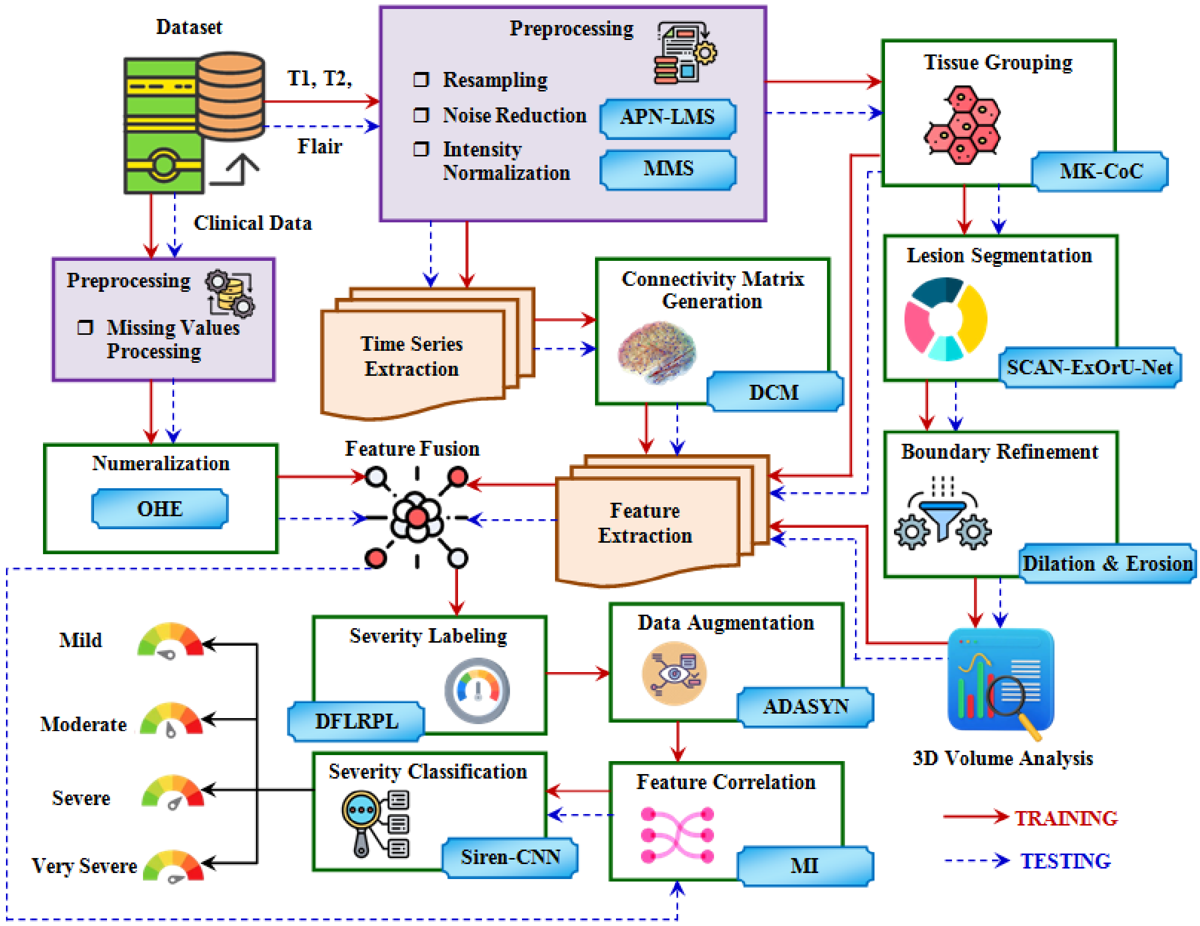

Figure 1: Block diagram of the proposed model

III. Performance Metrics

1. Accuracy

Accuracy measures the proportion of correctly classified instances out of the total instances.

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

2. Precision

Precision Measures how many of the predicted positive instances are actually positive.

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

3. Recall

Recall measures how many actual positive instances were correctly classified.

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

4. F-measure

It is the measure is the harmonic mean of precision and recall, balancing both metrics.

$$\frac{2*Re\,call*Pr\,ecision}{Re\,call+Pr\,ecision} \qquad (4)$$

5. Specificity

Specificity measures how many actual negative instances were correctly classified.

$$\frac{TN}{TN+FP} \qquad (5)$$

6. False Positive Rate (FPR)

Measures the proportion of falsely predicted positive instances out of actual negative instances.

$$\frac{FP}{TN+FP} \qquad (6)$$

7. False Negative Rate (FNR)

Measures the proportion of falsely predicted negative instances out of actual positive instances.

$$\frac{FN}{TN+FN} \qquad (7)$$

8. Processing Time

Measures the computational time required for the model to make predictions.

Start time – end time (8)

9. Mean Squared Error (MSE)

Measures the average squared difference between actual and predicted values.

$$\frac{1}{n}\sum_{j=1}^{n}\left|X_j - X_j'\right|^2 \qquad (9)$$

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10. Root Mean Squared Error (RMSE)

Square root of MSE, providing error in the same unit as the target variable.

$$\sqrt{\left(\frac{1}{n}\sum_{j=1}^{n} X_j - X'_j\right)^2} \qquad (10)$$

11. Silhouette Score

a = Average intra-cluster distance (distance between a point and other points in the same cluster).

b = Average nearest-cluster distance (distance between a point and points in the nearest neighboring cluster).

Silhouette Score measures how well clusters are separated, with higher values indicating better clustering.

$$b-a/max(a,b) \qquad (11)$$

IV. RESULTS AND DISCUSSIONS

The table 1 compares different segmentation methods based on accuracy, precision, Dice Score, and Jaccard Index. The Proposed SCAN-ExOrU-Net achieves the highest accuracy (99.91%) and precision (86.54%) but has the lowest Dice Score (0.1389).

Table 1. Accuracy,Precision,Dice score and Jaccard Index

Models	Accuracy (%)	Precision (%)	Dice Score	Jaccard Index
Proposed SCAN-ExOrU-Net	99.92	86.54	0.14	0.59
UNet	99.85	64.31	0.71	0.60
VNet	99.85	64.24	0.72	0.61
Segmenntation_Network (SegNet)	99.83	61.11	0.73	0.70
Residual_Network (ResNet)	75.90	6.11	0.87	0.79

Figure 2 compares the performance of different deep learning architectures (Proposed SCAN-ExOrU-Net, UNet, VNet, SegNet, and ResNet) using Jaccard Index and Dice Score, where ResNet achieves the highest values, followed by SegNet, while the proposed method performs comparably in Jaccard Index but lower in Dice Score. Figure 3 represents the accuracy and precision of the existing models with the proposed model.

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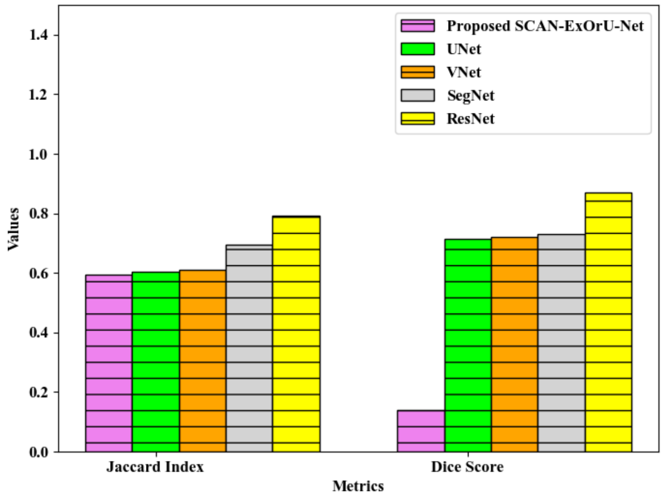

FIGURE 2. Performance of different models with the proposed model

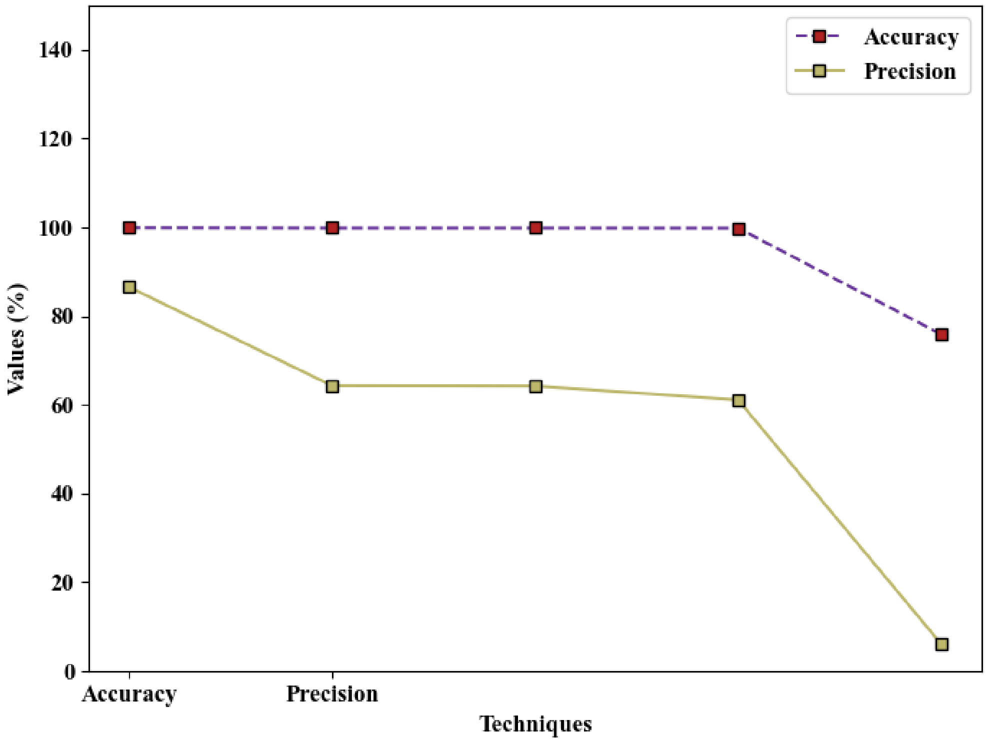

FIGURE 3. Accuracy and Precision values of different models

The figure 4 illustrates the computational time required for rule generation, fuzzification, and defuzzification across different fuzzy logic models. The Proposed DFLRPL model demonstrates the lowest processing time in all three stages, highlighting its efficiency. FL and SFL show moderate processing times, whereas Gaussian (GFL) and Triangular Fuzzy Logic (TFL) exhibit the highest times, especially in fuzzification. This suggests that GFL and TFL involve more computational complexity, making DFLRPL the most efficient model for fuzzy processing tasks.

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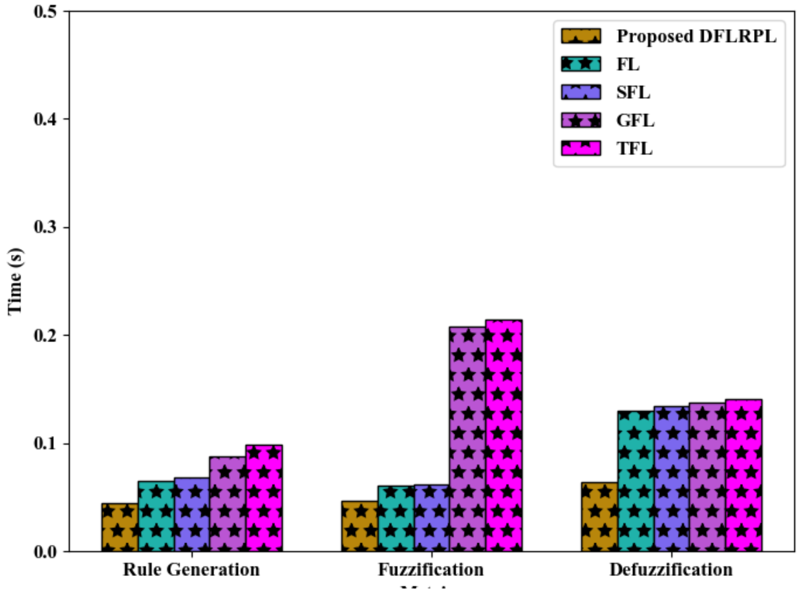

FIGURE 4. Performance of different models with the proposed model

The table 2 compares the performance of the proposed Siren-CNN with existing CNN, DCNN, AlexNet, and DNN models. Siren-CNN achieves the highest accuracy (99.25%), precision (98.52%), recall (98.51%), and specificity (99.50%) with the lowest false positive rate (0.01) and false negative rate (0.01), outperforming other models in classification performance.

Table 2: Performance metrics of the proposed model with exiting models.

Model	Accuracy (%)	Precisio n (%)	Recall (%)	F1-score (%)	Specificity (%)	FPR	FNR
Proposed Siren-CNN	99.25	98.52	98.51	98.51	99.50	0.01	0.01
CNN	97.95	95.90	95.91	95.91	98.63	0.01	0.04
Deep CNN (DCNN)	96.65	93.28	93.30	93.29	97.77	0.02	0.07
AlexNet	96.10	92.19	92.19	92.19	97.40	0.03	0.08
Deep_Neural_network (DNN)	95.40	90.81	90.79	90.79	96.93	0.03	0.09

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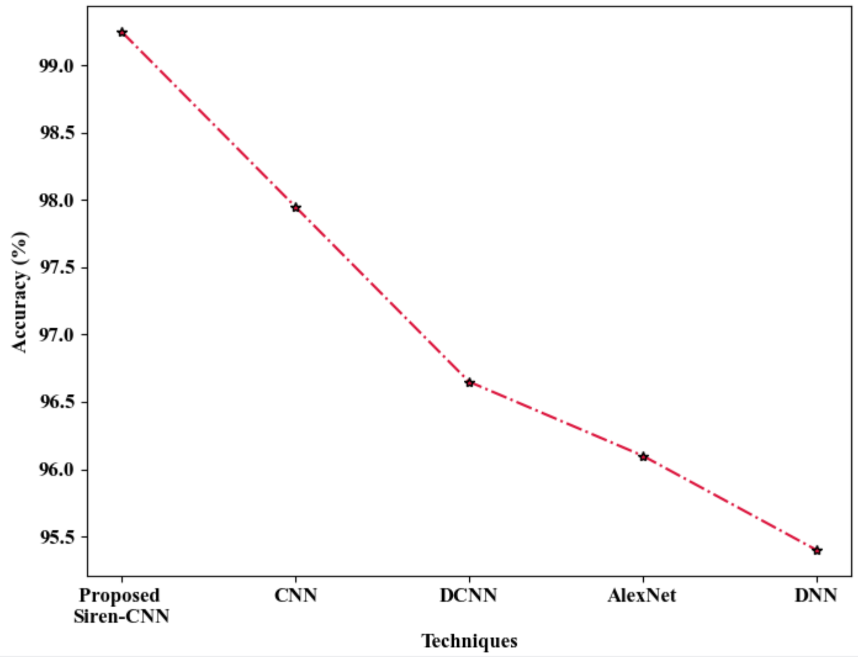

FIGURE 5. Comparison of accuracy values for severity classification with the existing methods

Figure 5 compares the accuracy of different deep learning techniques, including the Proposed Siren-CNN, CNN, DCNN, AlexNet, and DNN. The accuracy decreases progressively from the Proposed Siren-CNN (~99%) to DNN (~95.5%), indicating that the Proposed Siren-CNN outperforms traditional models. CNN and DCNN maintain relatively high accuracy, but AlexNet and DNN show a more noticeable decline. This suggests that the Proposed Siren-CNN offers superior accuracy for the given task, making it the most effective technique among the compared models.

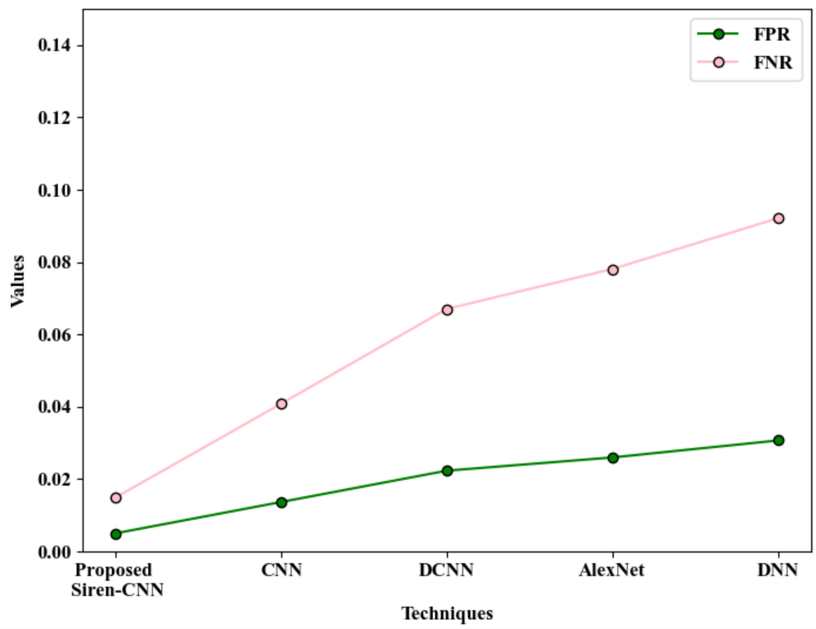

FIGURE 6. FPR and FNR values for severity classification with the existing methods

Figure 6 compares the False Positive Rate (FPR) and False Negative Rate (FNR) across different deep learning techniques. The Proposed Siren-CNN achieves the lowest FPR and FNR, while both rates increase progressively in CNN, DCNN, AlexNet, and DNN. This indicates that the Proposed Siren-CNN provides superior classification performance with minimal errors.

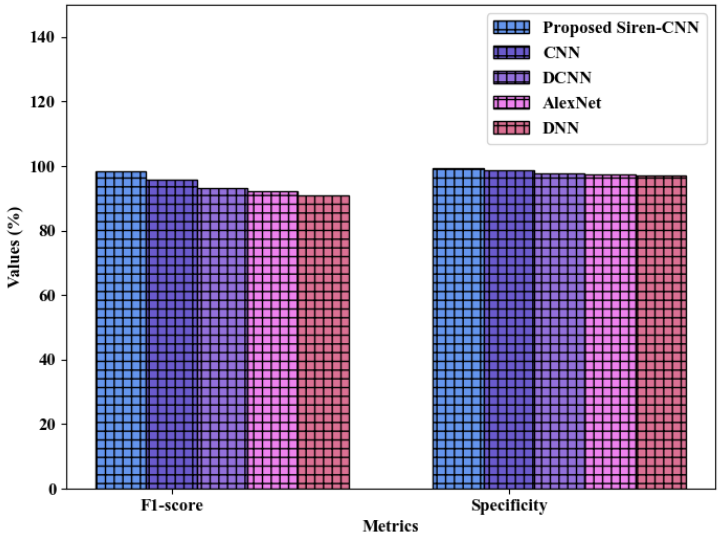

FIGURE 7 . F1-Scores and Specificity for severity classification with the existing methods

The confusion matrix shown in figure 8 illustrates the classification performance across four severity levels: Mild, Moderate, Severe, and Very Severe. The model shows high accuracy, with most predictions aligning with actual labels. Minor misclassifications occur, such as 5 Mild cases predicted as Moderate and 3 Moderate cases as Very Severe. Severe and Very Severe categories exhibit minimal misclassification. Overall, the model effectively distinguishes between severity levels, achieving strong predictive performance with minimal classification errors.

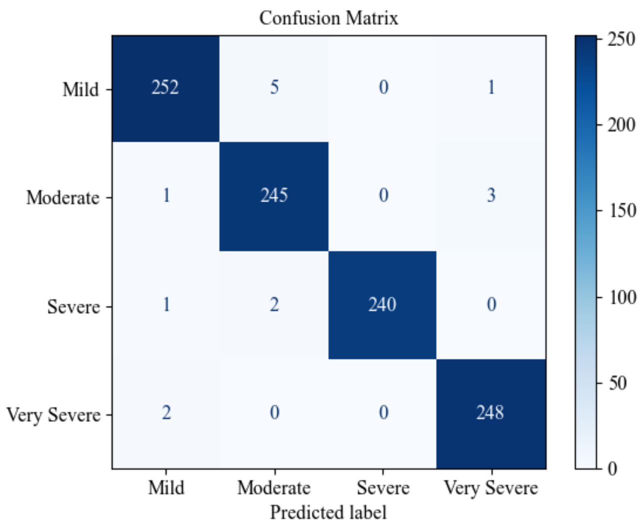

FIGURE 8 . Confusion matrix of the predicted model

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V. CONCLUSION

The proposed model demonstrates superior performance compared to existing techniques, achieving higher accuracy and efficiency in lesion segmentation. Experimental results validate the effectiveness of the SCAN-ExOrU-Net and the DFLRPL fuzzy logic model, showing improvements in precision, Dice score, and Jaccard index. Additionally, the model significantly reduces processing time for rule generation, fuzzification, and defuzzification. The confusion matrix confirms the high classification accuracy across different severity levels. Overall, this research presents a robust and efficient approach, enhancing segmentation accuracy and decision-making. Future work may explore further optimization and real-time applications in medical imaging and disease diagnosis.

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