IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Traitement du Signal
Vol. 39, No. 2, April, 2022, pp. 763-769
Journal homepage: http://iieta.org/journals/ts

Image Segmentation with Priority Based Apposite Feature Extraction Model for Detection of Multiple Sclerosis in MR Images Using Deep Learning Technique

Kalpana Narayan Rode*, Rajashekar Jangam Siddamallaiah

Dayanand Sagar College of Engineering, Affiliated to Visvesvaraya Technological University, Karnataka 560078, India

Corresponding Author Email: rodekalpana4@gmail.com

https://doi.org/10.18280/ts.390242

Received: 17 December 2021
Accepted: 26 February 2022

Keywords:
multiple sclerosis, deep learning, MR images, image segmentation, feature extraction, feature selection, apposite features

ABSTRACT

Multiple Sclerosis (MS) is a degenerative neurological disease caused by damage to the central nervous system's axons and myelin sheaths. MS lesions alter shape, position, and size over time in patients, therefore radiologists must be vigilant in detecting and evaluating MS lesions appropriately. Magnetic resonance imaging (MRI) has gotten a lot of attention from doctors for diagnosing MS, but there are other ways as well. The information provided by MRI modalities to doctors about the brain's anatomy and function is critical for making an MS diagnosis quickly. For automatic extraction of MS lesions from three-dimensional (3D) MR images, this work introduces a new feature selection approach. The approach described here can be used to treat a variety of MS lesions. MS MRI diagnosis takes a long time, is difficult, and is prone to human mistake. The design of a Computer-Aided Diagnosis System (CADS) based on Artificial Intelligence (AI) to diagnose MS incorporates standard machine learning and deep learning approaches. Traditional machine learning uses trial and error to extract, select, and classify features. Deep learning, on the other hand, uses deep layers with values that are automatically learned. In this research work, a Priority based Apposite Feature Extraction Model with Image Segmentation (PAFEM-IS) is proposed for segmentation and feature extraction. With proposed method, a large number of image attributes can be learned with little effort and bias on the part of the user. Apart from that, by using unlabelled data for feature learning, the classifier training can benefit from the significantly larger amount of generally available unlabelled data. The proposed model is compared with the traditional models and the proposed model exhibits better performance levels.

1. INTRODUCTION

An effective technique for disease detection has grown increasingly important as time has passed, and it is crucial to create a system that is both ideal and accurate. This Multiple Sclerosis (MS) [1] affects the white material of the brain and spinal cord and damages the nerves, which is why it is referred to as MS or an autoimmune disease. The myelin sheath that surrounds a nerve fibre protects it and facilitates in the passage of electrical signals between nerves [2]. The ability of the nervous system to function normally is contingent on the presence of myelin. Electrical impulses [3] pass along nerve fibres, and myelin acts as a barrier, preventing the impulse from exiting the axon while also increasing electrical resistance and therefore boosting signal transmission [4]. There are a number of cognitive, mechanical, and sensory problems that appear and can lead to neurological disease [5] when the myelin is removed. People may be familiar with MS, which is a demyelinating disease. MS is a condition that is still largely unknown to the public, and early identification is critical to slowing the progression of the disease [6].

Demyelination causes brain lesions [7]. As a result, brain lesion detection is crucial in MS research since it is used to monitor patient disease and indicates a potential future advancement [8]. For finding lesions, there are now manual or semi-automatic segmentation procedures, both of which are time-consuming and prone to inaccuracy. An international expert council approved the use of Magnetic Resonance Imaging (MRI) [9] in 2001 to diagnose patients with a subjectively isolated disease resembling multiple sclerosis. Multiple sclerosis is diagnosed by looking for evidence of disease progression over time and space, as well as ruling out other disorders with clinical and laboratory characteristics [10] similar to those of multiple sclerosis. When combined with clinical data, MRI can aid in the early and accurate diagnosis of multiple sclerosis [11]. MS patients can be identified almost exclusively by the use of MRI. Multiple sclerosis can manifest with a variety of physical and cognitive symptoms [12]. Patients with MS who suffer from cognitive impairment have a worse comfort and require more treatment. Diseases of the central nervous system such as MS, which is characterised by inflammation, demyelination, and axonal loss, often result in mechanical, sensory, visual, correlation, and cognitive dysfunction, are described as inflammatory and degenerative [13].

MS is a recurring neurological illness that can cause considerable disability in adults, but it also affects adolescents and young adults. MS instances have increased in recent years, and geography has a significant impact on the illness. MS affects more women than males, but men are more likely to develop the disease later in life. T2-weighted (T2-w) and contrast agents T1-weighted [14] neuroimaging methods are well-known for detecting MS lesions. The diagnosis of multiple sclerosis is now primarily reliant on MRI-derived characteristics. T2-w sequences demonstrate both fresh and persistent MS plaques as focused high-signal intensity areas, with water content illustrating all tissues [15].

MS relapses cause an annual rise in brain T2 lesion volume of approximately 5-10%. Inflammatory activity cannot be reliably detected with gadolinium-enhanced T1-w imaging. It is a progressive process that gets worse with the length of the dispute and proceeds at a rate of 0.7 to 1.5 percent of brain loss each year in this condition. The samples of MRI images of MS are shown in Figure 1.

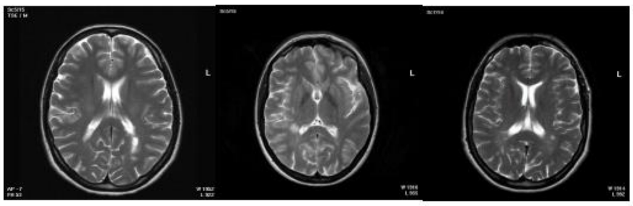

Figure 1. Samples of MR images of MS patient

Medical imaging is a technique of creating images of the inside of a body for use in clinical diagnosis and medical intervention. It aims to uncover underlying structures hidden underneath the surface of the skin and skeleton [16], as well as to make a diagnosis disease. There are many types of medical imaging technologies available today, each with advantages and limitations for obtaining information of human body. MRI is currently one of the most quickly evolving imaging modalities [17]. Its superb contrast resolution is by far MRI's most appealing feature. Even more than with Positron Emission tomography pictures, MRI can detect minute contrast variations in soft tissue [18].

An edge pixel is defined by two fundamental characteristics: edge strength, which equals the amplitude of the gradient, and edge direction, which equals the angle of the gradient. Actually, for a discrete function, a gradient is not defined at all; instead, the gradient, which may be defined for the perfect continuous image, is inferred using some operators. Among these operators are "Roberts, Sobel, and Prewitt." These types of operators are covered in the subsections. We use Laplacian-based edge detection to identify the type of shark fish in a sample of shark fishes. The zero crossovers of the derivative of the pixel intensities can be used to determine the Laplacian-based edge detection sites of an image [5]. This noise should be removed before doing edge detection [8]. The "Laplacian of Gaussian" is utilised to do this. For edge identification, this approach combines Gaussian processing with the Laplacian. The Laplacian of Gaussian edge detection procedure consists of three phases. The first is the picture object, which is a filter. Second, it improves the image object and, finally, it detects. This can be determined by using the shark case study. In this case, the Gaussian filter is utilised for smoothing, while the second derivative is employed for enhancement. The occurrence of a zero crossing, under this detection criterion.

The study of how to edit digital photographs with a computer is known as digital image processing. The system is made up of a small number of elements, each with its own position and value. Digital image processing techniques can be used to process images obtained from sources that people aren't used to recognising as images [19]. Among the different imaging techniques available are computer-generated pictures and ultrasonography. The brain is centred on the spine, which includes the spinal cord [20]. It is in charge of all bodily functions. The spinal cord is the primary route for brain impulses to travel to the rest of the body. However, because the spinal cord is shielded by the skull [21], studying its function and diagnosing illnesses is challenging.

Water is a fundamental component of the brain and is found in the cytoplasmic of neuronal cells as well as in the blood [22]. Lipids, the fat molecules that form up cell membranes, are abundant. When the myelin axons of the brain are normal, it is assumed that the patient has MS disease because the myelin axons are malformed [23]. The majority of commonly used methods for detecting white matter abnormalities in brain MR images still rely on expert detection and delineation with different degrees of computer aid. Image analysis will help us distinguish between normal and pathological tissue [24] and make disease monitoring easier if the best image analysis technology is used. Despite this, the substantial return on investment from our current research is making it easier to detect lesions in brain tissue and diagnose MS [25]. The sample MRI images with MS stages is shown in Figure 2.

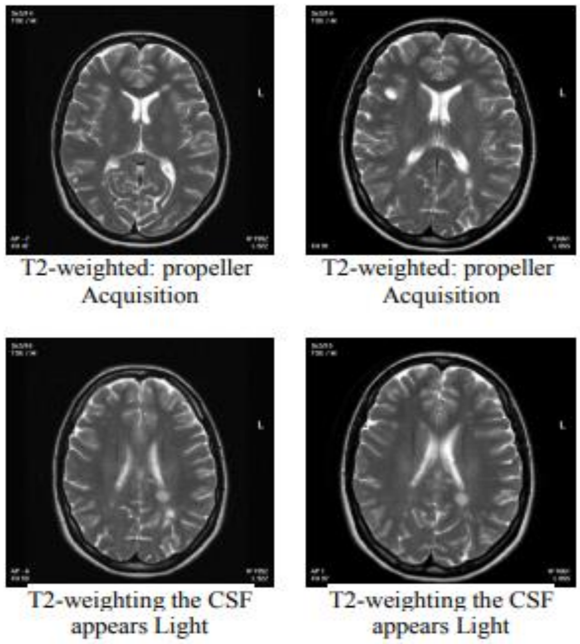

Figure 2. MS stages

2. LITERATURE SURVEY

The MS disease affects the nervous system and is characterised by relapsing-remitting nature and autoimmunity. As a result of damage to the myelin sheath, MS alters brain shape and structure [26]. Even more concerning is the possibility of MS leading to impairment in adolescents and young adults. Multiple sclerosis is a widespread disease in Europe, New Zealand, the US, and Australia. Because of its pathological characteristics, it has a significant impact on the lives of patients and their families.

Kaur et al. [1] examined the most up-to-date methodologies and provide future researchers with a list of the conclusions drawn from these methods. To classify and segment MS lesions, Shanmuganathan et al. [3] compared classification and segmentation approaches independently. They found that segmentation approaches deep learning based models outperformed the others in their comparison. Although deep learning methods were included in the previous review, there are other deep learning approaches that were not reviewed. The analysis of deep learning conducted by Gessert et al. [4] also didn't delve too deeply into the individual types of CNNs They just looked at generic methods like supervision strategy and input information processing strategy. The author examined MS lesion segmentation algorithms based on deep learning in this study in comparison with prior studies which categorised these approaches according to supervision strategy. The author separated these methods and classified into two CNN styles: patch-wise segmentation & semantic segmentation.

In the early stages of applying deep learning to the classification of MS lesions, the patch-wise segmentation technique is the easiest segmentation strategy to adopt. Classifier input is obtained by first segmenting an image into smaller patches, each patch being the classifier input. The classifier is used to traverse each image in turn. This approach makes better use of pixels' surrounding context. Using MRI as an input, Valverde et al. [6] created 15 X 15 X 15 patches on each voxel and run the input over two 3D convolution operation. A convolutional neural network and a softmax layer are then used to produce the probabilities for two possible classes. Many unnecessary calculations are incurred when patches overlap during patch-wise segmentation, which significantly reduces calculation performance. Zhao et al. [7] were the first to suggest semantic segmentation. An MRI volume or a big patch can be used as the input for semantic-wise segmentation. There will be no extra calculations due to overlapping patches in semantic segmentation. According to Alshayeji et al. [8], all of the MRI volumes are used as input in their work.

Deep learning is used by Badrinarayanan et al. [9] to learn about features, while random forest is used for categorization. In order to recognise frequent patterns, they first build a model on a vast amount of unlabelled data, and then create a customized model to the training subset. To identify each patch, Vaidya et al. [11] used 3D patches as input into a 3D convolutional network. To segment images from consistent multi-modal datasets, Havaei et al. [13] developed a Convolutional network. The method converts an image into an embedding space by converting it into a map. There are well-defined arithmetic calculations in this embedding space that can be employed for various inference modalities. Finally, the predicted segmentation can be derived from these estimated moments. This approach enhances the system's resistance to errors caused by erroneous input modalities.

Multiple photos, viewpoints, and time points are used as input in the Birenbaum and Greenspan [15] method. There are two parts to it. Before estimating the candidate voxel, FLARE and brain structures are used in the first stage, and multi-view CNN is used in the second stage to forecast the probability of a lesion in each MRI voxel. It's the first time deep learning has used segmentation based on time series data. To segment MS lesions, Gessert et al. [16] presented a cascade structure with two steps. To avoid an imbalance between favourable and unfavourable samples, they carefully pick the training data when building the model. Stage one produces voxels with a high likelihood of being lesions, and stage two determines if the voxels produced in Stage One are lesions further, and ultimately via threshold to generate binary masks of outputs from stage one.

Kervadec et al. [17] investigated the impact of intensity classification on prediction accuracy based on prior research. Heterogeneous single-channel MRI was used by La Rosa et al. [18] to simplify the well before processes and reduce processing time. They apply mathematical and morphological techniques to extract the lesion's features, and then train an MLP for classification to cut down on processing time. A probabilistic output of MS lesion locations is generated by applying RCNN to each modality's input image and using the recovered patches as the framework that can help in the RCNN output probability output of lesion occurrence. One way they propose to show how multiple MRI modalities are merged is through an adaptive neurofuzzy inference system. They then utilise this system to combine the output of every MRI modality in order to reach the final classification results.

Wong et al. [19] proposed a model to segment large and small lesions separately and proposed a new input vector to assist network training in order to tackle the problem of MS lesions having a huge range in size and is not differentiable. According to Zhang et al. [20], MS lesions are segmented by using 2D slices as output and a 2D transceiver network to prevent issues such as patch-wise techniques overlooking global information or overfitting 3D classification due to an imbalance in class. In order to avoid the overfitting of 3D-based segmented and the difficulty that patch-based segmentation cannot employ global information, Zheng et al. [21] concentrated on whole-brain slice-based segmentation. Additionally, it makes greater use of relevant data for segmentation via multi-level feature fusion. They use 2.5D stacked layers as input to increase segmentation performance and fully convolutional densely linked networks to segment MS lesions. 2.5D refers to images that have been placed orthogonally along three planes.

Recurrent neural networks (RNN) and long selective memory have intrinsic problems in capturing long-term dependencies, therefore Shin et al. [22] presented a recurrent slice-wise focus network that uses context information from MS lesions periodically. According to Aslani et al. [23], in order to deal with domain shift, the model should ignore domain-specific information by using a regularised network with an additional loss function. In order to increase the performance of MS lesion activity segmentation, Zhao et al. [24] proposed a 4D deep learning network. It increases the network's input by a 3D volume of historical time points and creates a novel multi-encoder-decoder architecture that employs convolutional-recurrent subunits for time aggregate. Aside from that, they looked at whether or not including a previous time point in the input would improve segmentation results.

3. PROPOSED MODEL

During the last three decays, various approaches for automatic image analysis and segmentation have been developed, allowing images to be split into their essential constituents. In order to locate the edges of objects, a wide variety of edge detection techniques are employed [27]. Edges are frequently found where two distinct areas of the image meet. Detecting brightness discontinuities at an object's edges is an image processing technique known as edge detection. In optical sensing systems, picture edge detection algorithms have been investigated extensively during the last three decades. Image segmentation, data extraction, and other computer vision and machine vision applications use it as well. Figure 3 represents the differences between Canny, Sobel, and Marr-Hildreth edge detection methods.

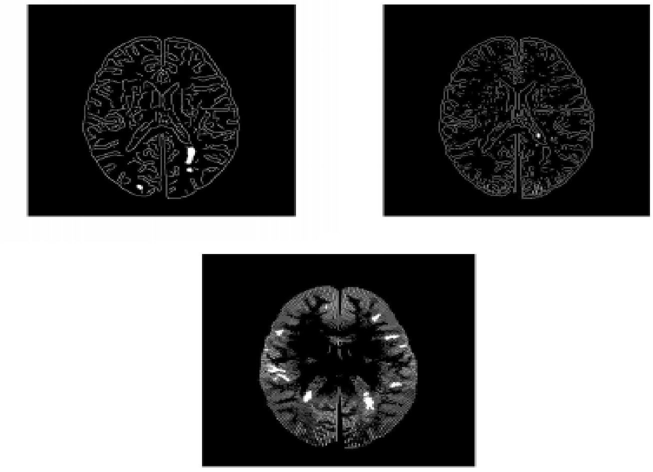

Figure 3. Differences between Canny, Sobel, and Marr-Hildreth edge detection methods

The image is considered as input and it initially undergo segmentation that divides the image into partitions. The segmentation process of the considered image is performed as

$$Segment(DS(I)) = \sum_{i=1}^{M}\sum_{j=1}^{N} pixel(I(x,y))_{ij}^{M} \left\|x_j - y_i\right\|^{N} \quad (1)$$

where, M is the maximum image dataset and N is the number of image types, X, Y are the neighbour pixels in a image I.

The pixel centres are calculated to identify the segment edge levels. The pixel centres are calculated as

$$Pixel\_Center(Segment(i)) = \frac{\sum_{i=1}^{M} Min(Segment(i))_{ij}^{M} X_j}{\sum_{j=1}^{N} \max(Segment)_{ij}^{N}} + \text{int}\,ensity(Pixel(I(x,y)) \quad (2)$$

The edge detection model is applied for accurate edge detection of the object in the image. The hidden layers are activated for edge detection for better accuracy levels. The hidden layers are activated as

$$HLayers(DS(I)) = \sum_{i=1}^{M}\sum_{j=1}^{N} \lambda_{ij}^{m}\left(\frac{1}{\min(Pixel\_Center)_N} \sum_{i\in N_i} \left\|X_j - Y_i\right\|^{M}\right) \quad (3)$$

Figure 4. Result when FCM applied after the canny edge detection

Figure 4 depicts the final outcome. After performing edge detection and enhancing accuracy using the proposed model is outlined there.

The pixels that are extracted from the image considered has to clear the noise levels from the pixels to accurately detect MS based on the features.

$$\text{Noise\_Rem}(I(i,j)) = \frac{H_{\max}}{W_{\min}} + I(i+H, j+W) + \theta \quad (4)$$

H is the histogram levels, W is the window vector intensity values, H and W is the height and width of the object in the image. The feature vector which represents weight of each pixel that is allotted for accurate MS prediction is calculated as

$$\begin{aligned}\text{Feat\_Vector}(I(i,j)) &= \int_{i=1}^{N} \text{HLayers}(\max(i,j)) \\ &+ \int_{j=i}^{N} \text{pixel}(\text{Noise}_{\text{Rem}}) \\ &+ \frac{1}{\lambda}\sum_{i=1}^{M} \text{Pixel\_center}_k^{T}(I_i - I_j^{N})\end{aligned} \quad (5)$$

where, λ represents the threshold intensity value. The priority allocation for the extracted pixel set is performed and based on the priority, the feature set is extracted that is useful in predicting of MS lesions. The priority allocation is performed as

$$\begin{aligned}\text{Pri}(\text{Feat\_Vector}(I(i,j))) &= \sum_{i=1}\sum_{j=i} \text{Feat\_Vector}(I) \\ &+ \lambda \sum_{i,j\in N} \min\,(\text{Noise\_Rem})_{i,j} \\ &+ \log \Pr(y_j = 1 | X; \text{Th}(W))\end{aligned} \quad (6)$$

The priority based feature cluster set is generated by considering the priority levels of the pixel set. The feature set is generated as

$$\begin{aligned}Final\_Feat\_Set(I(x,y)) &= \sum_{i=1}^{N} pri(Feat\_set(i,j)) \\ &- \frac{1}{\lambda}\left\{\sum_{i=1}^{N} HLayers(X_i, Y_j)\right\} + Th\end{aligned} \quad (7)$$

The prediction of MS is performed by considering the feature set extracted from the image. The prediction set contains the data that is having MS lesions. The final prediction set is maintained as

$$Pr\,e\,diction\_Set(DS(I)) = \frac{\sum_{i=1}^{N} Feat - Set_{ij}^{M}\left(X_{ij} + \frac{1}{N_T}\sum_{i,j\in DS(I)_N}(X - Y_i)\right)}{(1+\lambda)\sum_{i=1}^{N} max(Final\_feat - Set(I(X,Y)))} \quad (8)$$

4. RESULTS

Multiple sclerosis is a disease of the neurological system that affects the senses, vision, and mechanical function in persons who have MS. MRI has gotten a lot of attention from doctors for diagnosing MS [28], but there are other ways as well. When it comes to quickly diagnosing MS lesions, doctors rely on MRI modalities because they give them critical information about the brain's structure and function [29]. The proposed model is implemented in python and executed in GOOGLE COLAB. The dataset is available in the link http://biogps.org/dataset/tag/multiple%20sclerosis/. The proposed Priority based Apposite Feature Extraction Model with Image Segmentation (PAFEM-IS) Model is compared with the existing Machine Learning based Multiple Sclerosis Detection (ML-MSD) model. The proposed model is contrasted with the traditional models by considering parameters like Image Segmentation Time Levels, Segmentation Accuracy Levels, Pixel Extraction Accuracy levels, Feature Extraction Accuracy Levels, Features Considered, Detection Accuracy and Error Rate.

Segmentation is a discipline of image processing that focuses on splitting a picture into various sections based on the qualities and properties of the individual components [30]. Picture segmentation is the process of dividing an image into different segments that share comparable characteristics [31]. Image Objects are the sections of the image into which the image is divided. The proposed model takes less time to segment the image. The image segmentation time levels of the proposed and traditional models are shown in Figure 5.

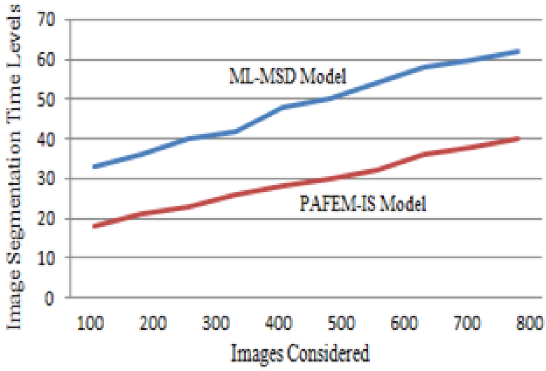

Figure 5. Image segmentation time levels

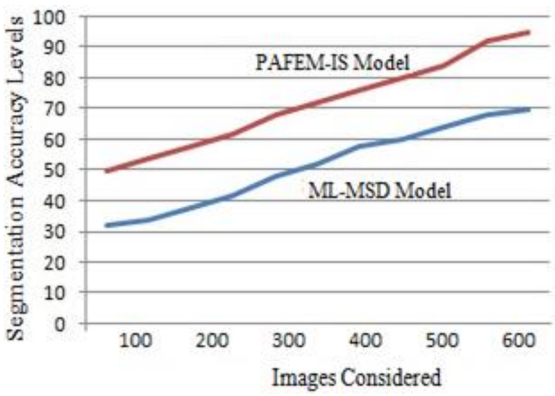

Figure 6. Segmentation accuracy levels

An alternate metric for evaluating segmentation is to merely provide the percentage of pixels in an image that were properly categorised as part of the segmentation. It is usual practise to provide the pixel accuracy for each class separately, as well as for the entire class set as a whole. The segmentation accuracy levels of the proposed model and traditional models are represented in Figure 6.

To achieve high segmentation efficiency, the study suggested a very efficient graph-based picture segmentation algorithm that employs a novel and rapid pixel extraction method. The images are segmented by modelling them as weighted graphs with nodes corresponding to super pixels; normalised cuts are then performed to the graphs to obtain the final segmentation. The pixel extraction accuracy levels of the proposed and traditional models are shown in Figure 7.

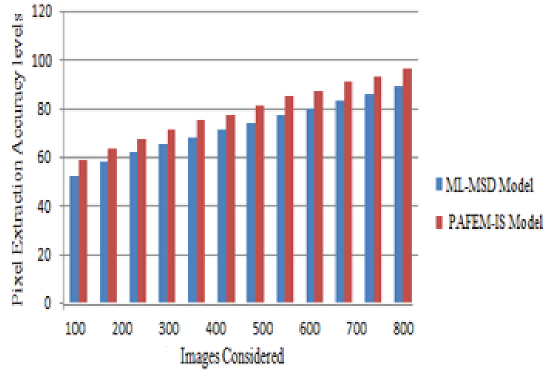

Figure 7. Pixel extraction accuracy levels

Dimensionality reduction can be performed with the help of feature extraction by separating an initial collection of raw data into more manageable groupings that can later be analysed. Because of the vast number of variables in these massive data sets, processing them requires a large amount of computing resources. The suggested model outperforms the existing model in terms of feature extraction accuracy. The feature extraction accuracy levels of the proposed and traditional models are shown in Figure 8.

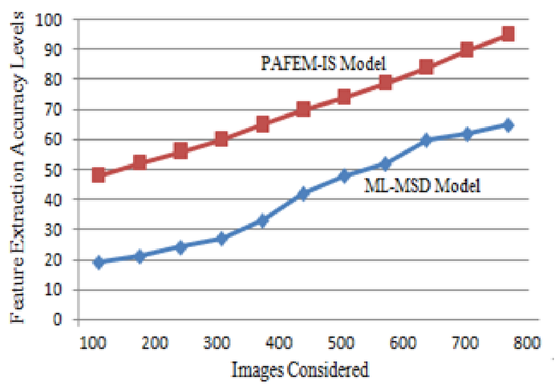

Figure 8. Feature extraction accuracy levels

The feature Selection technique generates new features that are a convolution of existing content and are utilised to generate new features. When comparing the new set of features to the previous set of features, it is obvious that the new set of features has different values. The primary goal is to minimise the number of features necessary to acquire the same quantity of data. The proposed model considers less features for MS Detection. The Features considered in the proposed and traditional models are represented in Figure 9.

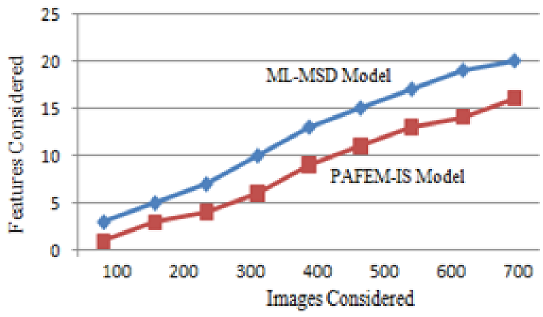

Figure 9. Features considered

The detection accuracy rate of the proposed model is high that represents the performance levels of the model. The detection accuracy levels of the proposed and traditional model are indicated in Figure 10.

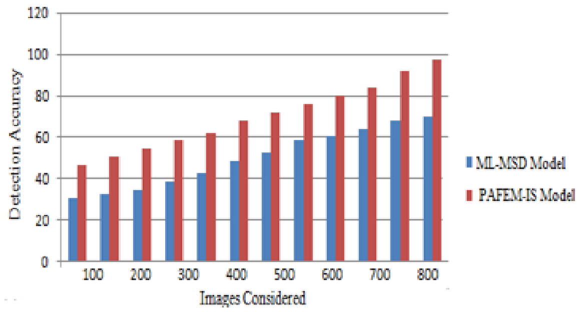

Figure 10. Detection accuracy

In mathematics, the error rate is measured as the ratio and is determined by dividing the number of reading by the total number of mistakes committed. The ratio is denoted by the number 1:20. The error rate of the proposed and existing models are shown in Figure 11.

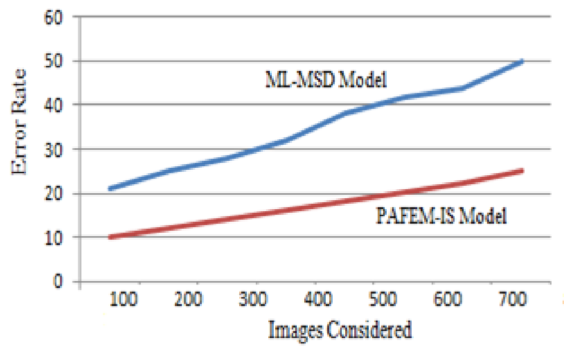

Figure 11. Error rate

5. CONCLUSION

Sclerosis is a disease that produces antibodies attacks the myelin sheath that covers the human nerve fibres, protecting them and facilitating the efficient transmission of data between the brain and body. Nerves become injured when they are not protected by this shell. Demyelination is the medical term for this type of damage. MS is a long-term condition that can impair the mind, spinal cord, as well as the eyes' optic nerves due to demyelination, which causes these lesions. This injury impairs the flow of messages between the brain and the body, resulting in symptoms such as weariness, numbness, visual impairments, cognitive issues, and so on. Message transfer will be slowed or obstructed, resulting in MS symptoms. No two MS cases are the same, and symptoms vary from patient to patient and depend on where myelin lesions have formed. As a result of these discrepancies, doctors rely on many diagnostic tools, including medical history, physical examination, neurological examination, and magnetic resonance imaging (MRI). In this research work, a Priority based Apposite Feature Extraction Model with Image Segmentation is proposed for segmentation and feature extraction for MS detection. Multiple sclerosis can be diagnosed and monitored using MRI since it is a great and important tool for identifying the disease. The proposed model detection accuracy is 97% that exhibits that the proposed model performance is better than traditional models.

REFERENCES

[1] Kaur, A., Kaur, L., Singh, A. (2021). State-of-the-art segmentation techniques and future directions for multiple sclerosis brain lesions. Archives of Computational Methods in Engineering, 28(3): 951-977. https://doi.org/10.1007/s11831-020-09403-7

[2] Ackaouy, A., Courty, N., Vallée, E., Commowick, O., Galassi, F. (2020). Unsupervised domain adaptation with optimal transport in multi-site segmentation of multiple sclerosis lesions from MRI data. Frontiers in Computational Neuroscience, 14: 19-19. https://doi.org/10.3389/fncom.2020.00019

[3] Shanmuganathan, M., Almutairi, S., Aborokbah, M.M., Ganesan, S., Ramachandran, V. (2020). Review of advanced computational approaches on multiple sclerosis segmentation and classification. IET Signal Process, 14: 333-341. https://doi.org/10.1049/iet-spr.2019.0543

[4] Gessert, N., Bengs, M., Krüger, J., et al. (2020). 4D deep learning for multiple sclerosis lesion activity segmentation. arXiv preprint arXiv:2004.09216.

[5] Aslani, S., Murino, V., Dayan, M., Tam, R., Sona, D., Hamarneh, G. (2020). Scanner invariant multiple sclerosis lesion segmentation from MRI. In 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI), pp. 781-785. https://doi.org/10.1109/ISBI45749.2020.9098721

[6] Valverde, S., Cabezas, M., Roura, E., et al. (2017). Improving automated multiple sclerosis lesion segmentation with a cascaded 3D convolutional neural network approach. NeuroImage, 155: 159-168. https://doi.org/10.1016/j.neuroimage.2017.04.034

[7] Zhao, S., Gao, Z., Zhang, H., et al. (2017). Robust segmentation of intima-media borders with different morphologies and dynamics during the cardiac cycle. IEEE J. Biomed. Health Inform., 22: 1571-1582. https://doi.org/10.1109/JBHI.2017.2776246

[8] Alshayeji, M.H., Al-Rousan, M.A., Ellethy, H., Abed, S. (2018). An efficient multiple sclerosis segmentation and detection system using neural networks. Computers & Electrical Engineering, 71: 191-205. https://doi.org/10.1016/j.compeleceng.2018.07.020

[9] Badrinarayanan, V., Kendall, A., Cipolla, R. (2017). Segnet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE Transactions

on Pattern Analysis and Machine Intelligence, 39(12): 2481-2495. https://doi.org/10.1109/TPAMI.2016.2644615

[10] Chaurasia, A., Culurciello, E. (2017). Linknet: Exploiting encoder representations for efficient semantic segmentation. In 2017 IEEE Visual Communications and Image Processing (VCIP), pp. 1-4. https://doi.org/10.1109/VCIP.2017.8305148

[11] Vaidya, S., Chunduru, A., Muthuganapathy, R., Krishnamurthi, G. (2015). Longitudinal multiple sclerosis lesion segmentation using 3D convolutional neural networks. Proceedings of the 2015 Longitudinal Multiple Sclerosis Lesion Segmentation Challenge, pp. 1-2.

[12] Commowick, O., Istace, A., Kain, M., et al. (2018). Objective evaluation of multiple sclerosis lesion segmentation using a data management and processing infrastructure. Scientific Reports, 8(1): 1-17. https://doi.org/10.1038/s41598-018-31911-7

[13] Havaei, M., Guizard, N., Chapados, N., Bengio, Y. (2016). Hemis: Hetero-modal image segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 469-477. https://doi.org/10.1007/978-3-319-46723-8_54

[14] Danelakis, A., Theoharis, T., Verganelakis, D.A. (2018). Survey of automated multiple sclerosis lesion segmentation techniques on magnetic resonance imaging. Computerized Medical Imaging and Graphics, 70: 83-100. https://doi.org/10.1016/j.compmedimag.2018.10.002

[15] Birenbaum, A., Greenspan, H. (2016). Longitudinal multiple sclerosis lesion segmentation using multi-view convolutional neural networks. In Deep Learning and Data Labeling for Medical Applications, pp. 58-67. https://doi.org/10.1007/978-3-319-46976-8_7

[16] Gessert, N., Krüger, J., Opfer, R., et al. (2020). Multiple sclerosis lesion activity segmentation with attention-guided two-path CNNs. Computerized Medical Imaging and Graphics, 84: 101772. https://doi.org/10.1016/j.compmedimag.2020.101772

[17] Kervadec, H., Bouchtiba, J., Desrosiers, C., Granger, E., Dolz, J., Ayed, I.B. (2019). Boundary loss for highly unbalanced segmentation. In International Conference on Medical Imaging with Deep Learning, pp. 285-296.

[18] La Rosa, F., Abdulkadir, A., Fartaria, M.J., et al. (2020). Multiple sclerosis cortical and WM lesion segmentation at 3T MRI: A deep learning method based on FLAIR and MP2RAGE. NeuroImage: Clinical, 27: 102335. https://doi.org/10.1016/j.nicl.2020.102335

[19] Wong, K.C., Moradi, M., Tang, H., Syeda-Mahmood, T. (2018). 3D segmentation with exponential logarithmic loss for highly unbalanced object sizes. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 612-619. https://doi.org/10.1007/978-3-030-00931-1_70

[20] Zhang, H., Valcarcel, A.M., Bakshi, R., et al. (2019). Multiple sclerosis lesion segmentation with tiramisu and 2.5D stacked slices. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 338-346. https://doi.org/10.1007/978-3-030-32248-9_38

[21] Zheng, Y., Sun, Y., Muhammad, K., de Albuquerque, V.H.C. (2020). Weighted LIC-based structure tensor with application to image content perception and processing. IEEE Transactions on Industrial Informatics, 17(3): 2250-2260. https://doi.org/10.1109/tii.2020.2980577

[22] Shin, H.C., Roth, H.R., Gao, M., et al. (2016). Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE Transactions on Medical Imaging, 35(5): 1285-1298. https://doi.org/10.1109/TMI.2016.2528162

[23] Aslani, S., Dayan, M., Murino, V., Sona, D. (2018). Deep 2D encoder-decoder convolutional neural network for multiple sclerosis lesion segmentation in brain MRI. In International MICCAI Brainlesion Workshop, pp. 132-141. https://doi.org/10.1007/978-3-030-11723-8_13

[24] Zhao, S., Wu, X., Chen, B., Li, S. (2021). Automatic vertebrae recognition from arbitrary spine MRI images by a category-Consistent self-calibration detection framework. Medical Image Analysis, 67: 101826. https://doi.org/10.1007/978-3-030-32251-9_35

[25] Carass, A., Roy, S., Jog, A., et al. (2017). Longitudinal multiple sclerosis lesion segmentation: Resource and challenge. NeuroImage, 148: 77-102. https://doi.org/10.1016/j.neuroimage.2016.12.064

[26] Chen, C., Dou, Q., Chen, H., Qin, J., Heng, P.A. (2019). Synergistic image and feature adaptation: Towards cross-modality domain adaptation for medical image segmentation. In Proceedings of the AAAI Conference on Artificial Intelligence, 33(1): 865-872. https://doi.org/10.1609/aaai.v33i01.3301865

[27] Gabr, R.E., Coronado, I., Robinson, M., et al. (2020). Brain and lesion segmentation in multiple sclerosis using fully convolutional neural networks: A large-scale study. Multiple Sclerosis Journal, 26(10): 1217-1226. https://doi.org/10.1177/1352458519856843

[28] Jégou, S., Drozdzal, M., Vazquez, D., Romero, A., Bengio, Y. (2017). The one hundred layers tiramisu: Fully convolutional DenseNets for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 11-19. https://doi.org/10.1109/CVPRW.2017.156

[29] Kazancli, E., Prchkovska, V., Rodrigues, P., Villoslada, P., Igual, L. (2018). Multiple sclerosis lesion segmentation using improved convolutional neural networks. In VISIGRAPP (4: VISAPP), pp. 260-269. https://doi.org/10.5220/0006540902600269

[30] Kumar, P., Nagar, P., Arora, C., Gupta, A. (2018). U-segnet: Fully convolutional neural network based automated brain tissue segmentation tool. In 2018 25th IEEE International Conference on Image Processing (ICIP), pp. 3503-3507. https://doi.org/10.1109/ICIP.2018.8451295

[31] Sudre, C.H., Li, W., Vercauteren, T., Ourselin, S., Jorge Cardoso, M. (2017). Generalised dice overlap as a deep learning loss function for highly unbalanced segmentations. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, pp. 240-248. https://doi.org/10.1007/978-3-319-67558-9_28