Journal of Theoretical and Applied Information Technology
15th March 2023. Vol.101. No 5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

MRI BASED CONVOLUTIONAL NEURAL NETWORK MODEL WITH ASSOCIATED FEATURE VECTOR MODEL FOR GRADE DETECTION OF MULTIPLE SCLEROSIS LESIONS

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ABSTRACT

Multiple Sclerosis (MS) patients who are receiving treatment must be monitored for new or expanded white-matter lesions. Multiple Sclerosis patients' multimodal brain Magnetic Resonance Imaging (MRI) images have been used to develop the first fully automated end-to-end deep learning approach for the prediction of future disability progression detection. Convolutional neural networks are used in nearly all new segmentation methods, each with a unique architecture. MRI scans are used to detect lesions in the brain and spinal cord that are characteristic of MS, and these scans are also used to track the disease's progress over time. The detection of lesions by hand takes a long time and is prone to error. It is difficult to detect the lesions manually, especially in the grey matter. Convolutional Neural Networks (CNNs) can be used to automatically segment lesions. In this research, a CNN model is used for the detection of Multiple Sclerosis. The use of CNN to extract features from flare MRI improves recognition performance. First, a segmentation-accurate CNN network is implemented, and then a false-positive reduction network is added to increase efficiency even further. CNN replaces the fully connected layer at the end of two parallel convolutional pathways, which are concatenated together. In this research, an Associated Feature Vector Model for Grade Detection of Multiple Sclerosis Lesions (AFVM-GD-MSL) using CNN is proposed. In terms of performance evaluation, CNN is a good choice because of its lack of noise sensitivity. No lesion segmentation was necessary to achieve the high detection rates achieved by CNN. As long as the variability is taken into account, this fully automated method yields accurate MRI analysis and grade classification.

Keywords: *Multiple Sclerosis, Convolutional Neural Networks, Segmentation, Feature Extraction, Grade Classification.*

1. INTRODUCTION

People suffering with Multiple Sclerosis (MS) have a degenerative disease that affects the spine, brain, and eyes. A myelin sheath protects the brain's axons [1]. There are two types of demyelination, both of which affect brain nerves by causing the myelin sheaths to come off and cause lesions to form. MS is a disease that primarily affects persons in their 20s to 50s, but it affects people of all ages. A wide range of physical and mental ailments can result from this condition, including exhaustion and memory loss [2]. In order to accurately diagnose and treat this condition, it is quite difficult due to its wide range of clinical manifestation. Magnetic Resonance Imaging (MRI) sequences can be used to identify these lesions [3]. Many biomarkers, such as the disease's volume and location, are critical for monitoring the disease's course [4]. The most typical technique in clinics is to manually segment these lesions by skilled radiologists, but this is exhausting, time-consuming, and error-prone [5]. Two raters manually segmented MS lesions in one slices of a MRI Image that is shown in Figure 1.

The most frequent kind of neurological disease in children and adults is multiple sclerosis. An inflammatory demyelinating disease, it is characterized by central nervous system lesions and axonal degeneration [6]. In the setting of MS, MRI is the primary diagnostic method. The widespread

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15th March 2023. Vol.101. No 5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

use of this imaging method has greatly advanced the understanding of a disease. Imaging techniques like as MRI are currently being utilized to diagnose multiple sclerosis [7], monitor disease progression, and evaluate treatment efficacy. Most commonly, the disease's lesion burden is quantified by counting how many and how large the disease-causing lesions are in the brain [8]. There is a link between the amount of lesions detected by MRI and the severity of the symptoms. Although the exact link between MRI-measured lesions and clinical results is unclear [9], it should be noted that Subclinical activity can also be measured and visualized using MRI [10]. Finally, it is responsive to the temporal fluctuations that are common in this condition.

Convolution Neural Networks (CNN) have been studied for their potential use in automatically segmenting MS lesions [11]. In place to enable 2D pixel classification and ultimately picture segmentation, CNNs learn subtle properties from the original image data. In other words, there isn't a single CNN model that works for all categorization problems and data. Because of the complexity of the data and the complexity of the application [12], an expert's input is required throughout the CNN model design phase. MS lesion segmentation is a complex topic that necessitates careful consideration of the CNN model [13] and training model. MS lesion segmentation in MRI can be difficult because of the poor contrast in the MR images, the borders between anatomical items are difficult to see in both size and location noise and inhomogeneity may be present in the MR picture of clinical quality [14].

In this paper, an Associated Feature Vector Model for Grade Detection of Multiple Sclerosis Lesions (AFVM-GD-MSL) using CNN is proposed for grade detection of MS lesions. The importance of the convolution layer resides in its ability to efficiently utilise several kernels of varying sizes in parallel. This smart strategy catches elements of varied magnitude in the data input without putting additional strain on the network. MS lesions can only be detected and segmented if healthy tissues are correctly segmented. There is a noticeable loss in healthy tissue volume, particularly grey matter, as a result of the condition.

Even in healthy individuals, MRI brain picture segmentation and grade detection is a difficult task. A number of factors contribute to the difficulty [15]. An introduction to the many types of noise artefacts that can be seen in MRI pictures is necessary. It is possible that these aberrations may provide outcomes that are unrealistic [16], with tissue and lesion regions appearing granular, fractured, or otherwise defying anatomical rules [17]. A second problem is that basic geometric primitives cannot accurately represent the intricate geometry of brain structures. Because of this, there is a great deal of variation in the shape of the tissue in different patients [18]. Finally, there might be significant overlap in the intensity distributions of distinct tissues. A challenging task is to segment aberrant structures, such as MS lesions. In terms of size, location, and shape, lesions are distinct from one another. In addition, because each MRI modalities reflects distinct physical features, the precise margins of the lesion may change between different Image channels.

2. TABLES AND FIGURES

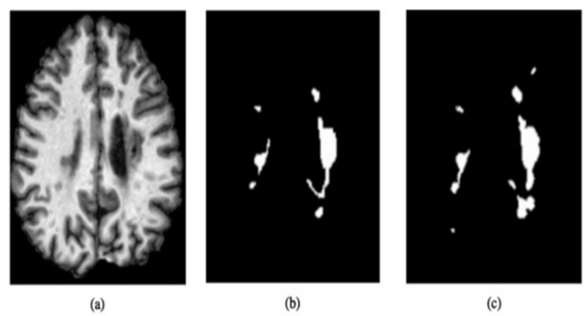

Figure 1: Manual segmentation Of MS lesions

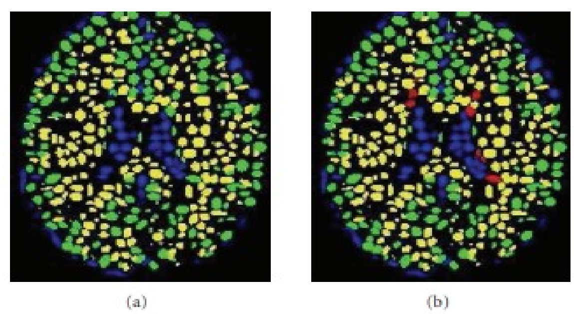

Figure 2: MS Lesion Identification

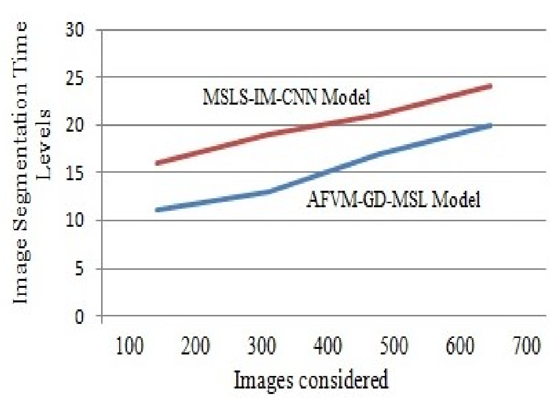

Figure 3: Image Segmentation Time Levels

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

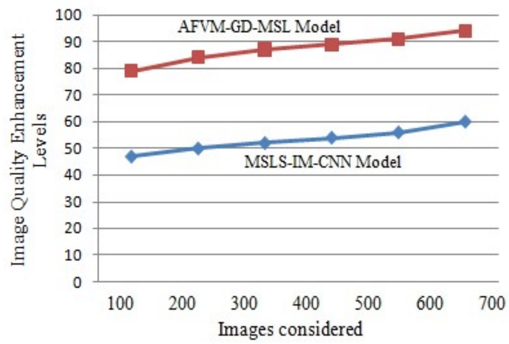

Figure 4: Image Quality Enhancement Levels

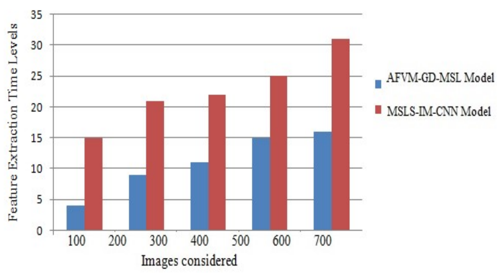

Figure 5: Feature Extraction Time Levels

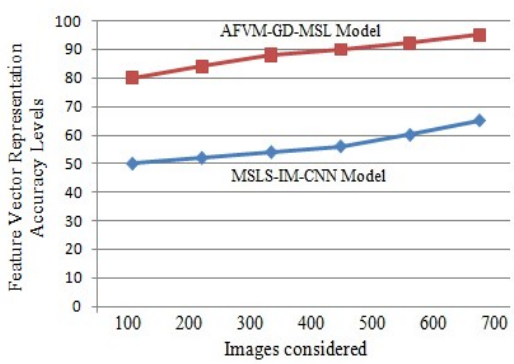

Figure 6: Feature Vector Representation Accuracy Levels

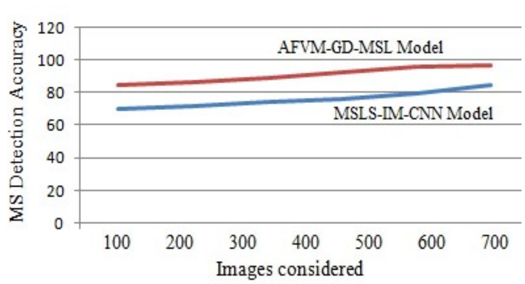

Figure 7: MS Detection Accuracy

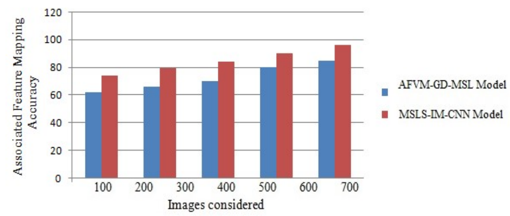

Figure 8: Associated Feature Mapping Accuracy

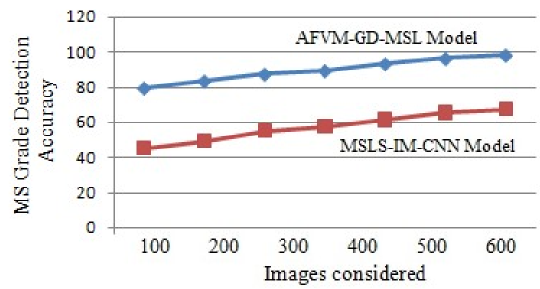

Figure 9: MS Grade Detection Accuracy

3. LITERATURE REVIEW

MS lesions in MR brain scans can be segmented using deep neural networks, which have demonstrated encouraging results over the last decade. Using a deep 3D neural encoder with shortcut connections in pathways, a novel design was suggested by Mina Qaisar et al. [1] for segregating MS lesions in MRI images. Using public data from the ISBI-2015 and MICCAI-2008 challenges, the approach was tested. Researchers compared their approach to MS lesion segmentation with five different approaches. Multiple sclerosis white matter lesions can be segmented using a unique design developed by Qaisar et al. [2]. Using 3D MRI patched from FLAIR & T1w modalities, a tumbled CNN model was presented. Using the MICCAI-2008 dataset, the proposed model scores outscored all other participant techniques.

In multicontrast MR images, Royetal.[4] presented a convolution neural network (CNN) using modulation scheme pathways to segment white matter lesions. Dual implementation for two different images are found in the first route of the CNN. The ISBI-2015 dataset was used to test this approach. Aslani et al. [5] proposed a new method for segmenting MS lesions using MRI images by utilizing a completely 2D CNN. The use of a Classification algorithm for the segmentation about MS lesions was examined by Huang et al. [6].

Tissue segmentation using a multimodal MRI database has showed encouraging results in recent studies. It was recently demonstrated that a deep multitask educational approach can execute a benchmarking tool on various BraTS datasets analyzed by Jin et al. [7]. Parallel decoder branches were used to claim an advantage over the classic V-Net framework. In addition to segmentation, the newly added encoder handles the auxiliary duty of distance estimation in order to produce a more precise segmentation boundary. With the introduction of a gamma factor and a total loss function, the focus is shifted from the backdrop and various weights are assigned to each kind of label to address the issue of category imbalance.

ME-Net was proposed by Yang et al. [8] utilizing the BraTS 2020 database and showed promising results. The four modal pictures of brain tumour MRI were encoded using four encoder architectures with skip-connections. The decoder was given a composite feature map as an input. There is a new nonlinear function called Categorical Dice that was developed by the authors, as well as varying weights for the various masks. Using a 3D supervoxel learning approach, researchers were able to segregate brain tumors with encouraging results. Segmentation accuracy was considerably improved with the additional information provided by multimodal MRI images.

The quality of a MRI scans can have a significant impact on the segmentation outcomes. An image segmentation task's precision is hampered by factors like low resolution, intensity fluctuations, and picture capture noise. Prostate cancer has been segmented using a deep framework described by Liu et al. [9]. A new version of 3D V-Net and bicubic interpolation dramatically improved segmentation results. For the segmentation of the prostate, bicubic interpolation of input data was used to enhance the key features. The segment of small yet distinct objects within MRI images has recently acquired popularity for attention-based approaches. A dilated attention system was utilized in a study to improve the appearance of scars on the left atrium.

MS lesions are difficult to detect and segment in MR images because of their diversity. The segmentation of prostatic zones has also been done with a CNN. They have developed a novel densely connected attention strategy to deal with the heterogeneity of prostate architecture. In multimodal MRI, Raschke et al. [13] established a statistical technique for analyzingtumor heterogeneity. The method described in this study makes no assumptions about the distribution of a MRI data or the location of tumors in the patient's body before collecting the data. For tumor segmentation of varied sizes and locations, this presents an advantage to the authors. An encoding network and a decoding network were proposed as part of the method, with the former being in charge of extracting image features and the latter being in charge of up sampling those maps. An ISBI-2015 dataset was used to test the FCNN.

4. PROPOSED MODEL

MS lesions come in a wide range of shapes and sizes. It is difficult to use machine learning algorithms to identify these lesions. An inception module-based CNN model is used to autonomously segregate MS tumors in brain MRI, as proposed. Large and small MS lesions are captured by filters of various sizes in the inception modules. Around the world, more than 2 million people are affected by MS, a demyelinating disease of the central nervous system (CNS). Sensory, motor, and cognitive capabilities are negatively impacted by MS. CNS lesions are a defining feature of MS. Gray and white matter (GM and WM) have MS lesions, however clinical scans that are obtained on a regular basis tend to show more of the WM lesions. Measures of disease status, patient care, and therapy efficacy, such as lesion load and tissue atrophy, are all based on these two concepts. Clinical trials involving several centers often use these indicators as secondary or major end goals. Tissue identification in MS has been the subject of several automated segmentation methods. While these procedures may have been useful, the majority of them focused exclusively on lesion segmentation. When applied to multi-center data, these approaches have shown relatively limited accuracy. GM, WM volumes have been demonstrated to be influenced by MS disease state in addition to lesions. The MS lesions are classified from the image considered that is shown in Figure 2. The red colored cells are identified MS lesions.

Automated segmentation is necessary for accurate calculation of tissue volumes because manual and semiautomatic methods might include significant operator bias. As a result, a brain tissue segmentation technique that is adaptable to data from several centersthat gives high accuracy is required. This is especially pertinent to clinical trials that collect a substantial volume of imaging data.There is a type of learning techniques known asdeep learning (DL) that employ neural networks to learn many levels of data representation. When using DL, the picture characteristics can be automatically learned from the input data. DL segmentation has been shown to be resilient against data heterogeneity and picture artefacts in multiple studies.In this research, an Associated Feature Vector Model for Grade Detection of Multiple Sclerosis Lesions (AFVM-GD-MSL) using CNN is proposed.

A kernel length and filter type must be carefully chosen in the CNN model so it can acquire all of the features that are relevant in object classification. Different filter sizes and pooling algorithms are used in various CNN layers to learn the most prominent characteristics in a dataset. The CNN model comprises of three convolution layers, the first two of which include 64 feature maps. In the final layer, a single feature map is used to forecast lesion and non-lesion voxels, respectively. The final output is created by concatenating the local features from all of the filters. For the inception module, employing a kernel to reduce the depth of the convolution layers is the primary goal. The spatial parameters are preserved in the convolutions, which can be used as needed. Using this technique in the inception module, the feature maps' dimensions can be reduced, resulting in decreased computing costs. The proposed algorithm is discussed clearly.

Algorithm AFVM-GD-MSL

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Input**:** Brain MRI image dataset {IMset[M]}

Output**:** MS Lesion Grade Detection Prediction Set

Step-1: Load an image Im from the Image dataset and perform the image segmentation. The segmentation process divides the image into equal partitions and then these segments are used for further analysis. The image segmentation is performed as

$$\operatorname{Im} g(P, I(i)) = \sum_{i=1}^{n} sqrt_i \left(P, I(i) \middle| \lambda_i, \Sigma_i Q\right)$$

$$Seg\,(I(i)) = \operatorname{Im}\, g(i) + split\left(P, \Sigma_i^x Q\right) \times \operatorname{Im}\, g\left(I(i); \lambda + \Sigma_i^N\ size\,(\operatorname{Im}\, g(i))\right)$$

Step-2: The pixels are extracted from the image segments and the pixel sets are established. The pixels are used for analysing the intensity levels to check for the similarity difference of the values range. The pixel extraction is performed as

$$pix\,(Seg\,(i)) = \frac{\sum_{i=1}^{N} \min\ \operatorname{int} en\,(P, Q) + \max\ \operatorname{int} en\,(P, Q)}{\sum_{i=1}^{N} size\,(IMset\,)} + Th$$

Step-3: The features are mined from the considered pixel set and the feature vector is generated that holds the most useful features in MS lesion detection. The feature extraction process is performed as

$$Feat\_extrac\_Set(Pix(i)) = \frac{\max(pix(seg(i)) + \sum_{i=1}^{N} grey(I(p,q)) + \lambda}{size(seg(N))} + Th$$

Step-4**:** The proposed model applies priority filtering on the feature vector so that the features are used for grade detection. The filtering model removes the noisy data and the features are arranged based on the priority levels. The process is performed as

$$\delta_i^N = \frac{1}{N_i} \sum_{t=1}^{N} \min(Feat\_extrac\_Set(\max(i)) + \frac{1}{Seg(i)} \sum_{i=1}^{N} \max \operatorname{int} ensity(I(i)) - \min \operatorname{int} ensity(I(i))$$

Step-5**:** The max pooling is applied to remove the unnecessary features and consider the most relevant features in the process of MS detection. The max pooling is applied as

$$Maxpool(Feat\_extrac\_Set(i)) = \frac{1}{\max(p,q)_N} \sum_{p=1} \sum_{q=1}^{N} \min(grey(\delta(i))) + \max(\operatorname{int} ensity(\delta(i))) + Th^{N}$$

Step-6: The cluster set is generated based on the feature vector that is updated after max pooling. The cluster set is generated as

$$Feat\_Vec[N(i)] = \frac{1}{Maxpool(\delta)} + \sum_i \frac{sim(Feat\_extrac\_Set(p,q))}{size(\delta)} + \left(p_i . q_i^N\right) + Th$$

Step-7**:** The classification of normal and MS lesions in the pixel set is performed and the prediction of the MS grade detection is done based on the size of the lesion. The MS lesion detection is performed as

$$\Pr ed(Feat\_Vec(i)) = \max_N \sum_{i=1} \delta + \frac{\max(Feat\_Vec(i), Feat\_Vec(i+1))}{size(Feat\_Vec[N])} + sim(p,q) + Th$$

Step-8**:** The grade detection is performed based on the size of the lesion and the grade is calculated by considering the threshold limit of the lesion and the prediction set is displayed. The process is performed as

$$Gr(\Pr ed(N)) = \frac{\Sigma_{i \in IMset} \Pr ed(p_i . q_i) + \Sigma_{j \in IMset} \min(Feat\_Vec(i, i+1_N)) + size(I(i))}{size(\Pr ed(Feat\_Vec(N))}$$

$$\left\{\begin{matrix} if & size(\Pr ed(i)) > Th & GradeL \\ Otherwise & & NIL \end{matrix}\right\}$$

}

5. RESULT

The use of convolutional neural networks to automatically segment MS lesions has been studied proposed in this research. The raw picture data is used by CNNs to learn minor properties that aid 2D pixel categorization, which ultimately leads to image segmentation. Nevertheless, there is no one-size-fits-all CNN model that can be used to solve every classifier model or every set of classification data. The nature of the system and the data need the incorporation of expert knowledge into the design phase of the CNN model. Complex issues like MS lesion segmentation and grade detection necessitate thorough consideration of the CNN architecture and training strategy. The proposed model is implemented in python and executed in Anaconda Spyder. In this research, an Associated Feature Vector Model for Grade Detection of Multiple Sclerosis Lesions (AFVM-GD-MSL) using CNN is proposed. The proposed AFVM-GD-MSL model is compared with the existing Multiple Sclerosis Lesion Segmentation in Brain MRI using Inception Modules embedded in a Convolutional Neural Network (MSLS-IM-CNN) Model.
The proposed model is compared with the traditional model in terms of Image Segmentation Time Levels, Image Quality Enhancement Levels, Feature Extraction Time Levels, Feature Vector Representation Accuracy Levels, MS Detection Accuracy, Associated Feature Mapping Accuracy and MS Grade Detection Accuracy. Image segmentation is a method of dividing a digital image into multiple subsets known as Image segments in order to decrease the image's dimensionality and facilitate further processing or analysis. The image segmentation time levels of the traditional and proposed model are shown in Figure 3.

Image quality enhancement is a procedure that's entirely up to the individual model that needs to improve the intensity levels of the image. Filtering, interpolation, sharpening, and magnification, as well as pseudo coloring, are all included in this process. The proposed model enhances the image quality before MS grade identification process. The Image quality enhancement levels of the proposed and traditional models are shown in Figure 4.

Linear combinations of existing features can be extracted via feature extraction. As a result, the new features will have values that are different from the original features. The fundamental goal is to collect the same information with fewer characteristics. The proposed model in less time extracts the most useful features to improve the accuracy in grade detection. The feature extraction time levels of the proposed and traditional models are represented in Figure 5.

Any vector containing data outlining an image salient features is a feature vector. Image processing features can come in many shapes and sizes. Each pixel's raw intensity value can be used to indicate a simple characteristic of an image. The feature vector representation accuracy levels of the proposed and traditional models are shown in Figure 6.

In conjunction with blood testing, MRI is the preferred method of diagnosing MS. In order to determine the amount of water in a tissue, MRIs use radio waves and magnetic fields. Detection of normal and pathological tissue and abnormalities can be found. The MS Detection accuracy levels of the traditional and proposed models are shown in Figure 7.

In order to structure and create value for the Feature Mapping is used as a technique for visualizing the big picture of a product feature for accurate analysis. The associated feature mapping accuracy of the proposed and traditional models are shown in Figure 8.

Active lesions can be distinguished from those that are dormant using an MRI scan. White areas appear on the image as active lesions when gadolinium contrast fluid is injected. There is a good chance that a non-illuminating lesion is older than 3 months old. The proposed model detects the MS grades in less time with more accuracy. The MS grade detection accuracy levels of the proposed and traditional models are indicated in Figure 9.

6. CONCLUSION

Mutiple sclerosis is an inflammatory disease of the central nervous system characterized by the existence of lesions in the brain and spiral cord. In MS patients, MRI has emergred into an important preclinical technique for detecting and predicting long-term disability and therapy response. A convolutional neural network was used to classify an enhancing lesion on unenhanced MRI data. To obtain reliabln e predictions , this categorization was conducted for each segment , and the segment scores were combined using a fully connected network.

Manual detection of lesions is time-consuming and imprecise. For reliable grade detection of MS

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

lesions, the suggested Associated Feature Vector Model for Grade Detection of Multiple Sclerosis Lesions (AFVM-GD-MSL) employing CNN is applied. The CNN network is utilized to precisely segment lesions, while the network structure aims to remove false positives to increase efficiency. The system is composed of two parallel convolution channels, one of which is connected to the other, and the fully connected layer is replaced by CNN in the end.

The proposed method is based on the concept of two convolutional neural networks(CNNs), with the first CNN detecting probable lesions and the second CNN correcting false positives, delivering increased accuracy and speed. The use of CNNs instead of the fully linked layer results in increased performance because the fully connected layer consumes memory. With higher accuracy levels, the features can be lowered in the future, as can the training time complexity.

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