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MULTIPLE SCLEROSIS MR IMAGES DENOISING MODEL FOR ACCURATE CLASSIFICATION USING CONVOLUTION NEURAL NETWORK

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ABSTRACT

Multiple Sclerosis (MS) is a chronic neurological disease characterized by demyelination in the central nervous system, where Magnetic Resonance Imaging (MRI) plays a vital role in lesion detection. However, accurate identification of MS lesions remains a challenge due to the presence of various noise types such as Gaussian, speckle, and salt-and-pepper noise, which reduce image clarity and distort lesion boundaries. Existing denoising and segmentation approaches, including traditional filters and Convolution Neural Networks (CNN) based models, have shown limitations, filters often compromise edge preservation, while many deep learning techniques require extensive pre- and post-processing, leading to reduced efficiency and inconsistency in lesion classification. This gap in the literature highlights the need for an approach that can simultaneously suppress noise and retain essential lesion details for reliable segmentation. To address this, the study proposes a Hybrid Convolutional Neural Network with Pixel Batch Normalization (HCNN-PBN) that integrates denoising and segmentation in a unified framework. The novelty of this model lies in its ability to preserve critical structural features during the denoising process through pixel batch normalization, thereby improving lesion classification accuracy compared to conventional CNN-based denoising methods. The research introduces new knowledge by demonstrating that denoising and segmentation can be optimized together in a hybrid CNN framework without significant loss of detail, reducing computational complexity while enhancing diagnostic reliability. Experimental results validate that the proposed HCNN-PBN model outperforms existing CNN-based approaches in terms of denoising accuracy, segmentation accuracy, filtering efficiency, and processing time, thereby offering a more effective solution for automated MS lesion detection in MRI images.

Keywords: *Multiple Sclerosis, Magnetic Resonance Imaging, Convolution Neural Networks, Denoising, Segmentation. Pixel Normalization.*

1. INTRODUCTION

There are many different types of lesions that can be found in the central nervous system (CNS), and Multiple Sclerosis (MS) is one of them [1]. Over 3.5 million people worldwide are affected by these lesions, which are most common among those in their 30s and 40s. This is a lesion that affects more women than men. White matter (WM) abnormalities are the most common type of lesion found by MRI [2]. By employing weighted-T2 pictures [3], they can be spotted more precisely. It requires a radiologist to reach and separate the lesions physically and visually in order to do this type of diagnostics [4]. However, in real time, where MRI brain scans are often found to be progressively volumetric, this manual technique delivers less accurate results. Slice-by-slice segmentation can be used to deal with this situation [5], but it is labor-intensive and subject to bias and

substantial inter- as well as intra-rate variability. MS lesions can be viewed in a variety of ways, including those that are only visible on T2w [6], those that are enhancing, and those that are black holes. Automated segmentation of WM lesions is a complicated operation that relies heavily on the parameters chosen [7]. A number of researchers had proposed new models involving automatic segmentation of MS lesions [8], where each technique lacks any criteria that could lead to erroneous results.
An MR image is a useful, non-invasive imaging technology for capturing and analysing various bodily tissues, which aids the doctor in the detection of disease and the subsequent treatment [9]. The brain is the main and most difficult organ in the body to study, necessitating the use of rather sophisticated procedures [10]. The MRI technique is the most commonly utilised method by doctors to diagnose and treat Regression analysis [11], lexis learning, boosted decision forests and patch based models are some of the prior efforts that have been led in this context for MS severeity detection. The MS lesions in MRI is shown in Figure 1.

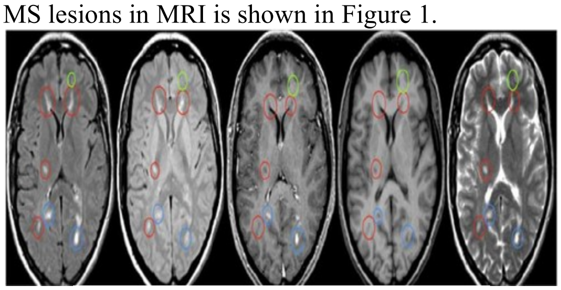

Fig 1: MS Lesions In MRI Example Images

The image capturing and transmission process generates noise. Due to the magnetic field, thermal noise and random picture fluctuations are generated, as is impulse noise during transmission [12]. Grayscale images have minute differences in pixel intensity, making it difficult to accurately segment them. Pre-processing MR images for noise reduction is critical. Also included in the MR images are noises like Rician distributions noise of MR images [13], Gaussian noise, Speckles noise, and Salt-and-Pepper noise. To reduce these types of noise, a variety of filters and techniques are employed [14]. There have been a number of approaches to MS segmentation, and research is underway to develop an automated system [15]. The quality of a MR images has a direct impact on the accuracy of segmentation. It's unfortunate, because MR images suffer from noise when they're captured and transmitted [16]. Denoising the photos may increase the difficulty of segmentation by degrading the image quality. Denoising an image while preserving its quality and important elements is the goal of this research denoising technique. We propose a novel method of successful MS MR image denoising utilising CNN in this research. The proposed method preserves the image's quality and important elements while denoising.
Remote sensing employs denoising techniques to eliminate white Gaussian noise and salt and pepper noise [17]. Image denoising technologies have helped suppress noise in MRI photographs since it can reduce the quality of the evidence in the image. The initial image processing filters were linear, non-linear, and non-adaptive filters [18]. There are six types of noise reduction filters: linear, non-linear, adaptable, wavelet-based, partial differential equation (PDE), and total variation. Linear filters reduce noise by multiplying nearby input pixels by corresponding output pixels [19]. Filters that are non-linear preserve edge information while suppressing noise at the same time. The non-linear filter is frequently used instead of the linear filter in filtering applications [20]. Linear filtering is regarded to be a poor filtering approach since it does not maintain edge information.

In order to improve the accuracy of MS lesion classification, this research aims to create a HCNN-PBN model for MRI denoising and segmentation. The suggested model incorporates pixel batch normalization to improve feature preservation during denoising, which is different from traditional filtering and current CNN-based methods. This allows for the effective reduction of noise while crucial lesion features are preserved. As a long-standing issue with previous methods, this methodology guarantees that the segmentation accuracy is unaffected by the preprocessing stage. Image denoising accuracy, segmentation accuracy, computational efficiency, and image filtering performance are the main result measures that are examined in this work. All of these are compared with current CNN-based MRI denoising models. Offering a more trustworthy framework for automated MS lesion detection and classification, the study brings a fresh perspective to medical image analysis by tackling the dual challenges of noise removal and structural detail retention. The denoising process using CNN is shown in Figure 2.

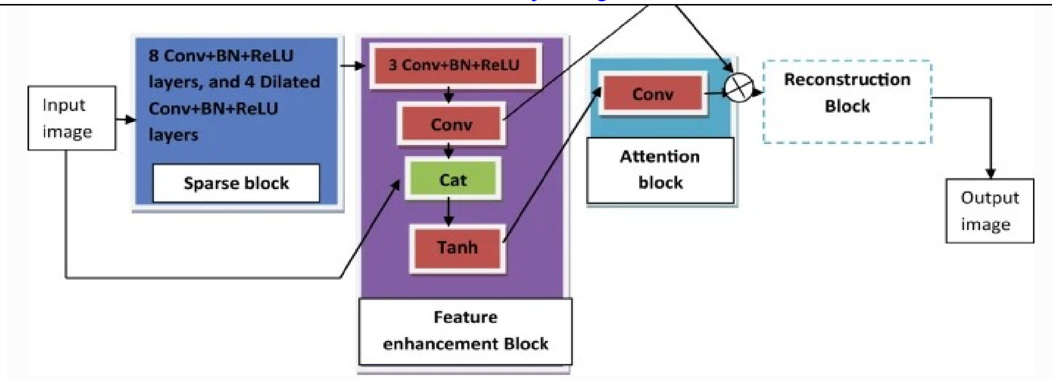

Fig 2: Denoising Using CNN

That CNN is able to learn noise patterns and picture patches successfully is not a matter of debate [21]. However, a vast amount of training examples and image patches are generated as a result of this learning process. The weighting mixtures for each noisy patch were merged with the local subtasks. Image patches were sorted by complexity and the k network was trained by using modified multi - layer perceptron auto encoders to do this [22]. Feature extraction, interpretation, and fusion are all sub-networks of the network. Extracting feature patches from higher dimensional feature maps is the primary function of the feature extraction sub network [23]. The cascaded approach was used to learn maps from multi scale data and to produce tolerant errors in sound estimation [24]. This sub-network finally integrates the full noise map to generate estimation [25].

This research's scope is limited to the creation of an MRI lesion identification model for MS that makes use of deep learning for denoising and segmentation. In order to classify MRI images accurately while reducing noise, the study suggests a HCNN-PBN. Since MRI scans are considered the gold standard for multiple sclerosis diagnosis, this study uses just MRI as its imaging modality. The scope of this research does not include other diagnostic approaches including genetic, biochemical, or clinical investigations.

This research places the study firmly within the realm of medical image processing, with a focus on denoising and segmentation of MRI images for the purpose of MS identification. Neurological lesions can be detected primarily using MRI, and the authors stress that MS is a chronic disease. The accuracy of segmentation and classification is greatly diminished when MRI images are contaminated with various forms of noise, such as Gaussian, salt-and-pepper, speckle, and impulsive noise. Additionally, radiologists must expend a lot of effort and make mistakes when making manual diagnoses. In order to address these issues, the research suggests a HCNN-PBN to accurately classify MS lesions from MRI images by denoising them while keeping crucial structural information.

Medical imaging and laboratory testing are used to detect MS disease in patients. One of the more specialized types of medical imaging is MRI [26]. Internal body tissue images can be viewed, and injuries and disorders to various parts of the body can be identified using an MRI. MRI is frequently used to detect lesions in the brain caused by multiple sclerosis [27]. Lesions and plaques in the brain can be seen clearly with MRI scans. To detect MS lesions in MRI, the shape, position, and size of the lesions vary greatly from person to person [28]. The use of MRI in the early detection of disease in people at high risk is critical. For this reason, there has been a lot of research into MS disease diagnosis [29]. Diagnosis can be performed in three ways: manually, semi-automatically, or automatically [30].

Detection of lesions relies on manual examination. Because manual approaches take a long time and need a lot of mental concentration, MRI scans were used in two or three dimensions to develop semi-automatic and automated systems for lesion diagnosis. The MS diagnosis system is broken down into pre-processing, feature extraction and classification. To better compete with other state-of-the-art methods, numerous CNN and other approaches have been presented in recent years for the automated detection MS disease lesions. The methods that have been proposed thus far have flaws. Pre-processing such as segmentation is required for some methods while post-processing is required for some ways in order for them to be classified more accurately. Furthermore, issues like blurring have not been addressed in the majority of solutions.

This research work limits its emphasis to deep learning for MRI-based multiple sclerosis

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detection, with a particular emphasis on picture denoising, segmentation, and classification. It doesn't go into more general methods of diagnosing multiple sclerosis, such genetic, biochemical, or clinical testing, or other forms of medical imaging, like computed tomography or positron emission tomography scans. Algorithmic enhancements to picture preprocessing and lesion diagnosis are the only things covered, not comprehensive patient care or treatment plans.
The research's lack of consideration for other diagnostic methods, such as clinical testing, analysis of cerebrospinal fluid, genetic and biochemical markers, and MRI-based identification of MS lesions, is one of its main weaknesses. Despite MRI's prevalence as a lesion identification technology, limiting the suggested method to its application in a purely MRI environment could limit its practical utility. Dependence on noisy MRI datasets is another problem. Despite the fact that HCNN-PBN is specifically engineered to denoise images, there are instances where the removal of noise diminishes or blurs crucial picture information. The segmentation accuracy and diagnostic reliability could be compromised if crucial structural information is lost as a result of this trade-off.

Another obstacle is the computing load of the deep learning model that has been developed. Massive datasets, powerful computers, and a lot of optimization time are needed for CNN-based architecture training. Such processing burden might restrict practical deployment in real-time medical applications where quick decision-making is vital. Limitations in the dataset and problems with generalization further limit the model. Since the training and evaluation are carried out on a specific dataset, the results may differ when used with pictures obtained from different MRI machines, environments, or patient groups. The validity and scalability of the suggested approach are very susceptible to variations in picture acquisition procedures.

2. LITERATURE SURVEY

One of the most pressing and unanswered questions in medical image analysis is how to reliably identify MS lesions in MRI scans. Despite the numerous denoising and segmentation methods that have been suggested, there are still certain things that need fixing, according to the research. The therapeutic value of traditional linear and non-linear filters is limited because, although they reduce noise, they muddy lesion boundaries and degrade fine structural details. While adaptive filtering and wavelet-based approaches do a better job of feature preservation, they are computationally intensive and quite sensitive to parameter settings, hence their performance varies among different MRI datasets. The accuracy of lesion identification has recently been improved by methods based on deep learning, specifically CNNs. Nevertheless, current CNN-based models frequently necessitate substantial pre- and post-processing stages, rely heavily on big annotated datasets, and face challenges in achieving a balance between denoising efficiency and the retention of vital lesion features. Despite better segmentation performance, studies like Brosch et al. (2015) and Valverde et al. (2017) still have issues with losing edge information, having large processing costs, and not being very adaptable to varied imaging procedures.

For MR image denoising, there are both non-linear and linear approaches. The linear filtering technique is accomplished by updating the pixel's value across the weighted sum of nearby pixels, thus suppressing the noise. This technique is effective at reducing noise, but the clarity of the image suffers. The photos are negatively affected by the non-linear filtering procedure, but the image edges are preserved. Some of these methods have advantages and disadvantages, for example, the Adaptive Diffusion Filtering (ADF) method may denoise and preserve tiny features of MR images while still keeping the edge details intact. However, the adjustment of variable number can change the results totally. The scaling coefficient is biassed when denoising with Wavelet-based approaches. The coefficients are made independent of the signal using the Chi-square distribution approach proposed by Tripathi et al.[1]. Still, there are issues with wavelet thresholding and scalability assurance. The non-local filtering approach proposed by Havaei et al. [2] to calculate the average of photons local in feature space. At the expense of more computations, better outcomes were gained. To retain contour information, Valverde et al. [4] introduced Biletral Filtration (BF) based on the notion of domain filtering. Unlike ADF, this approach is non-iterative, giving it an advantage over ADF. If the new value of a pixel is calculated in BF by narrowing its spatial window to preserve large-scale structures, non-local filtering's performance can be enhanced. The Gaussian filter is the most often used technique for MRI denoising, however the image quality suffers as a result. A strong statistical approach known as Linear Mean

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Square Errors (LMSE) is being used to quantify Rician noise, and the recovery of MR pictures improved, but at a higher computational cost.
Brosch et al. [5], the Rician noise is reduced using a block-wise comparison approach. Denoising is also aided by an algorithm known as the Low Rank Tensorflow Estimator (LRTE), which outperformed several other current methods. Real-world issues could not be solved with this approach due to the nuclear norm reduction of LRTE, which treats all singular values identically. To remove Rician noise, fuzzy logic was used with Quasi Mean to detect non-local homogeneous pixels and remove the noise, but this method has been unable to properly retain the edges. Segmentation approaches based on CNNs are more intuitive. Each pixel is predicted using a basic CNN model, which is then improved upon by feeding prior predicted values into a second CNN model.
According to Vaidya et al. [7], processing is carried out in distinct models, and the forecast is formed after integrating the input from all CNN models into an overall prediction. The smoothness of the segmentation process is ensured by the employment of a global super pixels segmentation at the end of this procedure. Convolution is used in conjunction with the same global supervision mechanism at each stage of a network. Using both global and regional contextual information, as well as convolution at the final layer, a CNN-based technique is proposed by Cerasa et al.[9]. This method of segmentation uses the analogy of rainwater generating lakes to detect boundary points at high gradient sections of the picture, and it is one of the most widely utilized for segmentation.

Ponnada et al. [11] developed an SVM-based classification method that used inputs from the three MRI images as inputs to accomplish classification. Demographic and clinical data, lesion geometry, and imaging intensity statistics are all taken into account in this study in order to arrive at an accurate categorization. The geometrical aspects of the MRI images are measured using Minkowski functionals. In order to establish a useful decision-support system for doctors, Walton et al.[14] presented a procedure based on differential development for the automatic detection of probable lesion classification in a real-world MS database. Specific information extracted from a dataset as an IF-THEN principle collection of ANDs, all made by Along with literals on the data to demonstrate, was indicated to consumers by the DEC device. As a result of the studies, it was concluded that the methodology used was effective, and the results of the analyses validated this conclusion by showing a higher percentage of correctly classified participants than in the past..

An adaptive vocabulary learning algorithm and sparse representation was used by Howard et al. [15] to automatically classify MS lesions from MRI. They examined the effects of training dictionaries tailored to the lesions and the various brain tissues, including CSF, WM, and GM, that were shown to be fit. When it came to classification, the size of the lexicon played a critical impact in how well information could be conveyed. An approach based on the degree of difficulty of the concealed information allows the dictionary size to be customized for each class. When tested on medical records, the proposed algorithm proved more accurate results. To aid in the classification of lesions in MS diagnosis and observation, Chung et al. [16] presented an evolutionary fuzzy methodology. An evolutionary-fuzzy algorithm was used to adjust task forms for each semantic correlate with the standards, and professional's medical information was validated using linguistic factors and standards as well as fuzzy principles.

Burt et al. [18] developed a computer vision method for the detection of multiple sclerosis (MS). On MRI scans, the lesions caused by MS could be seen. CV algorithms offered a variety of methods for identifying individuals. The grey level founder network was used in this study to extract surface features from MRI images' grey tone circulation. As a classifier, the author used a sophisticated feed forward neural network. A biogeography-based optimization approach was then selected to train the classifier. With cross-validation, the approach achieved a specificity and sensitivity of 90% and 91%, respectively. In general, the classifier was shown to be less accurate than existing MS lesion detection techniques.

The correct diagnosis of Multiple Sclerosis lesions in MRI scans continues to be a tough problem, despite tremendous advancements in medical image processing. Conventional filtering approaches and previous CNN models, among other denoising and segmentation algorithms, sometimes make compromises between reducing noise and preserving important picture information. Noise reduction is achieved by linear and non-linear filters; however, these methods may distort lesion boundaries or impair edge information. In a similar vein, numerous deep learning models succeed in better segmentation, but they fail to consistently classify lesions due to variability in size, intensity, and position. Several approaches, as pointed out in the literature, necessitate intricate pre- or post-processing stages, rendering them computationally demanding and less flexible for use in real-time clinical practice. These shortcomings highlight the necessity for an improved method that efficiently and effectively preserves image quality while achieving denoising precision and dependable lesion segmentation.

This research aims to address the primary problem of developing an automated framework for denoising and segmenting MRI images in order to improve the accuracy of MS lesion diagnosis without compromising important structural information. This research proposes a new approach to the problem by combining traditional denoising and segmentation methods with a HCNN-PBN model.

Due to these restrictions, there is currently no comprehensive model available that can denoise MRI data while maintaining essential structural elements necessary for precise MS lesion segmentation. Timely treatment and illness management are directly impacted by diagnostic accuracy, making the closure of this gap crucial. To address this, we provide HCNN-PBN, a new architecture that combines denoising and segmentation with pixel-level feature preservation, to meet this need. A more robust and clinically relevant solution for automated MS lesion detection can be achieved by demonstrating that denoising and structural preservation can be achieved concurrently. This study builds upon prior deep learning advancements and introduces new knowledge, thus justifying its existence.

3. PROPOSED METHOD

Noise in MRI is of great concern as it can deceive and result in erroneous diagnoses of patients. In addition to aesthetically distorting the recovered pictures, noise is also an issue when undertaking quantitative scanning on the MRI [31]. The value of MRI declines if an area or specific region suffers from a poor signal-to-noise [32]. Thus, there is a demand for an efficient MRI reconstruction phase, where denoising algorithms are applied to noisy pictures in terms of improving both qualitative and quantitative metrics of MRI [33].
As predicted, the noise in unprocessed MR images was typically dispersed, spatially consistent and white [34]. In the same way that MR image processing is sensitive to noise, MR images are also very sensitive to faults in image acquisition and transmission [35]. An MR image's quality is impacted by the presence of Gaussian noise as well as salt and pepper noise. Feature extraction, reduction, and classification of processed MR images can all be negatively affected by a poor MR image. It is impossible to avoid Gaussian noise and Impulse noise in magnitude MR images due to their widespread distribution. Many filters are employed to reduce Gaussian noise because of its analytical tractability both in spatial and frequency domains. The bright and dark parts alternate in salt and pepper noise, which is considered impulsive noise. It is common for impulsive noise to be digitized as absolute values in a picture because it is often larger than the image signal itself.
To begin, the MS detection system is given with the available datasets. After that, a number of MRI preprocessing methods are employed. Finally, a DL architecture that is both reliable and accurate is developed for the purpose of automatically detecting MS. The MS detection general process is illustrated in Figure 3.

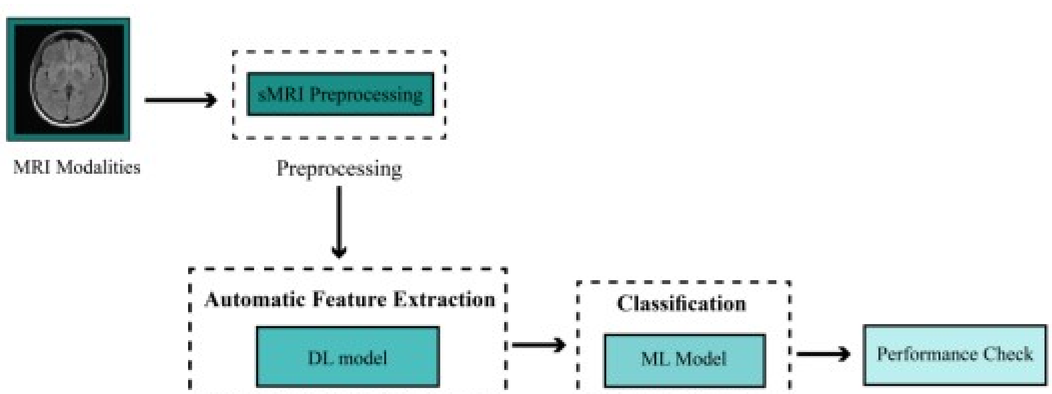

Fig 3: General Architecture For MS Detection.

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An important step in the image analysis process is image denoising. It is possible to remove noise from a corrupt image while keeping the essential details intact using the process of image denoising. Degradation functions and additive noise affect the observable image in the majority of image processing issues. The proposed model procedure is represented in Figure 4.

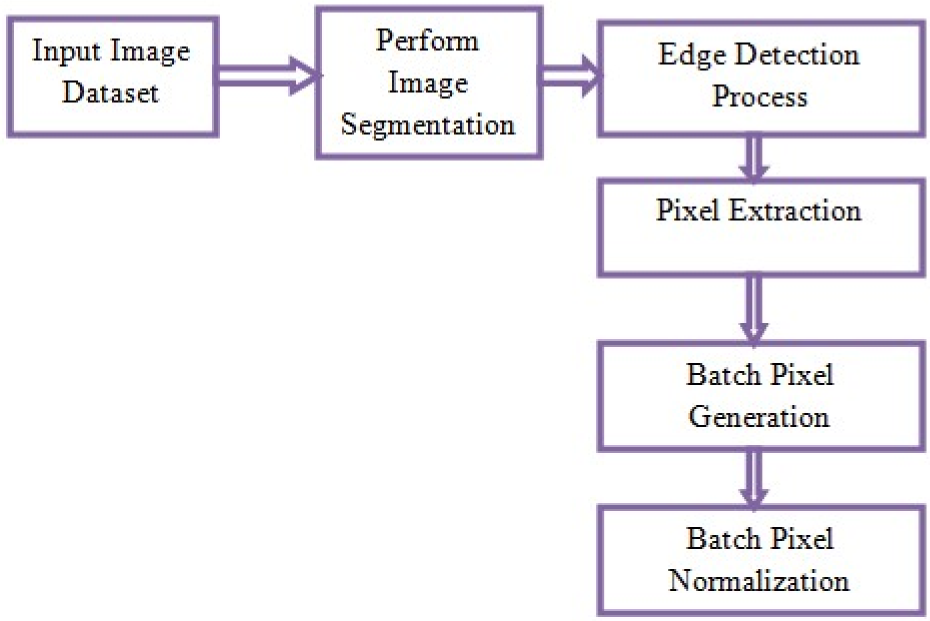

Fig 4: Proposed Model Framework

The proposed Hybrid CNN model with Pixel Batch Normalization model is explained clearly in the algorithm.

Algorithm HCNN-PBN

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Step-1: Load the MRI image from the dataset and perform the process of analysis to extract the features after performing denoising process. The image loading is performed as

$$\mathrm{Im}\,ageset[P] = \sum_{i=1} get\,\mathrm{Im}\,age(MS\,\mathrm{Im}\,ageDataset) + getsize(\mathrm{Im}\,age)$$

Step-2: The image segmentation is performed for splitting the image into multiple partitions for better extraction of pixels from each segment. The image segmentation is performed as

$$Iseg(\mathrm{Im}\,age(i)) = \frac{sizeof(image)}{2 * Th} \sum_{i=1}^{M} \left\| getPixel(x,y) \right\| + \sqrt{\max Intensity(x,y) + pixelRange(i)}$$

Here Th is threshold value, x,y are the adjacent pixels of the image considered.

Step-3: The edge detection from the segments is performed so that accurate outline of the MS objects is recognized for pixel extraction. The edge detection is performed using the mathematical representation as

$$EdgeSet(ISeg(i)) = Iseg_i(x,y) + \frac{\lambda(x,y)}{sizeof(Iseg)} - \min Intensity(x,x+1) + \sum_{i=1}^{SegCount} \max Intensity(x,y) + sim(x,y)$$

Here λ is the Threshold value of a segment maximum intensity value. The SegCount is the total number of segments of an image.

Step-4: The pixel extraction is performed in the segments generated. The pixels inside the detected edges only will be extracted. The pixel extraction is performed as

$$PixSet(IMGS[N]) = \left(\frac{getIntensity(x,y)+\omega}{sizeof(EdgeSet)}\right) + \max Intensity(x,y) + \min GrayLevel(x,y)$$

Here ω is the intensity added to the pixels to improve quality of the image. The getIntentisy model extracts the intensity levels of the pixel in the segment.

Step-5: The pixels extracted are grouped as batches as similar intensity values are grouped as a batch. The batch pixel set is generated as

$$BatchPixSet[M] = \sum_{i\in PixSet} \sum_{x,y} \frac{|\max(sim(x,x+1)^{\lambda})|}{sizeof(Iseg)} + \min(sim(x+1,x+2)) - \omega$$

Step-6: The CNN model is applied for the pixel normalization so that identification of MS will be accurate. The hidden layers process the pixel intensity values and the disisimilar values are not considered. The similar values are normalized so that the detection of severity will be easy and accurate. The batch pixels are normalized as

$$PixNorm(BatchPixSet(i)) = \frac{\max(\lambda(sim(x,y))) - \omega}{sizeof(Iseg) + sizeof(PixSet)} + \min(Pixelrange(i,i+1))$$

}

4. RESULTS

Noises such as Gaussian noise, salt and pepper noise, and speckle noise are common in Magnetic Resonance Imaging (MRI). As a result, obtaining an accurate image of the brain is an extraordinarily difficult process. In order to proceed with the diagnosis, it is imperative that an accurate image of the brain be obtained. MR image processing encompasses several different subfields, one of which is de-noising. MRI, which plays a critical role in clinical diagnosis and produces high-quality 2-D and 3-D images of the body, is influenced by noise. The proposed research considers MRI Images for denoising for accurate MS detection. The proposed model is implemented in python and executed in Google Colab. The dataset is considered from the link https://www.kaggle.com/competitions/dat300-ca2-autumn2019/data. The proposed Hybrid CNN model with Pixel Batch Normalization (HCNN-PBN) model is contrasted with the existing Convolution Neural Network for denoising of MRI scans (CNN-DMRI) model [1].

The image will be loaded from the image dataset and then processed for the denoising operation. The MRI image is considered for the detection of MS. The image loading time levels of the existing and proposed models are shown in Figure 5.

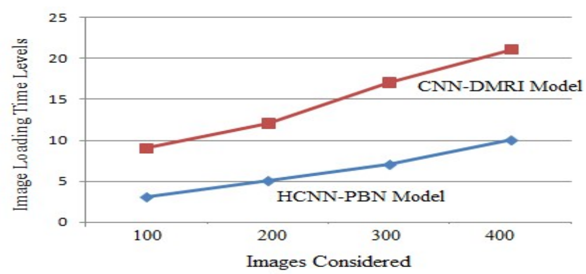

Fig 5: Image Loading Time Levels

An image is segmented into smaller subsets called Image segments, which simplifies continued processing or evaluation of the image by lowering its overall complexity. Segmentation is the process of labelling individual pixels. A label is applied to each visual element or pixel that belongs to a specific category. The image segmentation time levels of the proposed and traditional methods are shown in Figure 6.

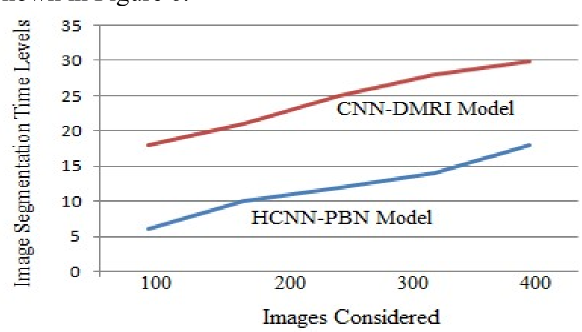

Fig 6: Image Segmentation Time Levels

A label is assigned to each image by the network in an image classification task. The shape of the object and which pixels correspond to which objects are two procedures in segmentation. Adding a class to each pixel of an image is the best way to accomplish this task in this circumstance. Segmentation is the term for this process. A segmentation model provides a great deal more information about a picture than does a simple pixel count. The image segmentation accuracy levels are shown in Figure 7.

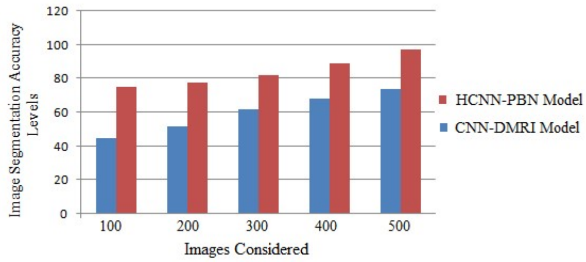

Fig 7: Image Segmentation Accuracy Levels

It is possible to alter an image's appearance by changing the colors of its pixels. Applying filters can improve the contrast and give a range of distinctive effects to images. Applying filters can improve the contrast and give a range of distinctive effects to photographs. Filters in image processing are mostly used to suppress either the picture's high or low frequencies, i.e., to enhance or detect the image's edges, in order to smooth the image. The Figure 8 represents the image filtering accuracy levels.

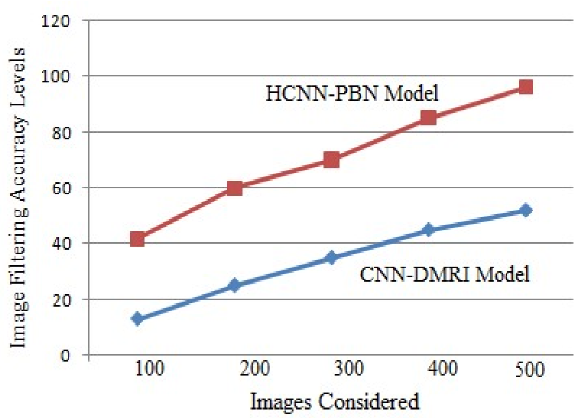

Fig 8: Image Filtering Accuracy Levels

Denoising is a key task in the field of computer vision and image processing, where the ultimate purpose is to approximate the original image by reducing noise from a noisy image. Gaussian noise can be used to an image as a means of removing noise from the image. The Figure 9 illustrates the denoising process time levels of the traditional and proposed models.

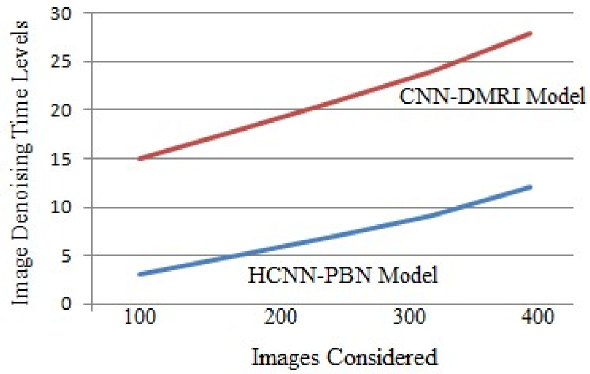

Fig 9: Image Denoising Time Levels

Modern cameras generate a lot of noise when taking pictures, resulting in blurry, washed-out photographs. Work must be done to reduce noise without sacrificing the quality of images. Denoising an image means removing artefacts and restoring the original image. Since high frequency components such as noise, edge, and texture are difficult to identify in the denoising process, certain details may be lost in the denoised images. In general, obtaining high-quality photos by removing noise from noisy photographs is a pressing issue in today's world. The image denoising accuracy levels are represented in Figure 10.

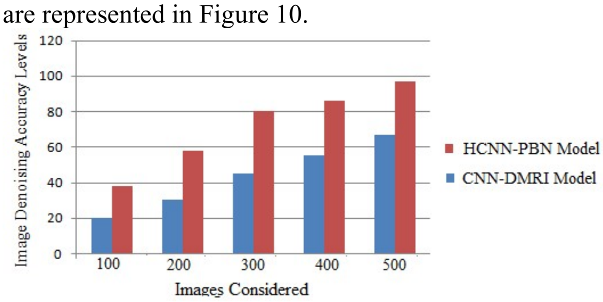

Fig 10: Image Denoising Accuracy Levels

5. CONCLUSION

Noise greatly impacts segmentation and classification reliability in MRI images, making successful Multiple Sclerosis lesion detection a recurring challenge. This research sought to address this issue. The limitations of previous methods include high computing requirements, complicated pre- and post-processing steps, trade-offs between noise suppression and preservation of fine lesion details, and wavelet-based denoising and CNN-based segmentation models, among others. This research extends the state-of-the-art by developing a HCNN-PBN. This unified deep learning system integrates denoising and segmentation, making it a scientifically significant addition. The suggested HCNN-PBN uses pixel batch normalization to

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maintain structural fidelity while effectively decreasing Gaussian, speckle, and salt-and-pepper noise, in contrast to previous CNN-based models that run the risk of blurring lesion borders during denoising. The suggested model beats state-of-the-art CNN-DMRI methods in experimental testing on many result metrics, including as processing time, segmentation accuracy, filtering efficiency, and denoising accuracy. Noise in the MRI process affects images as they are being acquired and transmitted. The image's ability to accurately segment the MS region is hampered by noise. However, the image quality may be impacted by denoising, and in certain cases, crucial components of the image may be lost as a result of denoising. In this research, a new strategy for reducing MR image denoising while preserving picture quality and essential characteristics was developed. It was found that applying the Deep CNN approach alone outperformed both Deep CNN and Gaussian in terms of performance. In this research, Hybrid CNN model with Pixel Batch Normalization is proposed that accurately performs the denoising model and segmentation of MRI images for accurate feature detection. In future, enhanced morphological operations can be applied to enhance the image quality for better operations for MS detection.

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