SRSSN: A Pre-processing Technique for Enhancing MRI scans for Parkinson's Detection

Ketna Khanna[1], Sapna Gambhir[2], Mohit Gambhir[3] & Parkinson's Progression Markers Initiative*

[1]Ph.D. scholar, Computer Engineering, India

J. C. Bose University of Science and Technology, YMCA, Faridabad, Haryana, India

[2]Associate Professor, Computer Engineering, India

J. C. Bose University of Science and Technology, YMCA, Faridabad, Haryana, India

[3]Director, Innovation Cell, India

Ministry of Education, India
Haryana, India, 121002

*See PPMI author list at http://www.ppmi-inf o.org/authorslist/

Abstract:

Parkinson's disease (PD) is an irreparable neurological disorder that results in motor disabilities. The early onset yields mild non-movement related symptoms associated with Parkinson's. PD in later stages results in motor signs like tremors, seizures, balance disabilities, rigidity etc. which worsens with time. Hence, early diagnosis is a necessity to ensure minimum damage. PD is normally detected manually by neurologists via inspection of its symptoms which may lead to an incorrect diagnosis. Researchers have proposed various automated PD inspection techniques based on MRI scans. However, the artefacts and noise may be induced during MRI acquisition which may deteriorate its quality and may change its anatomy that may lead to misdiagnosis. Hence, pre-processing is a vital phase that may reduce the effect of artefacts and noise thereby enhancing the diagnostic capability of a model. This paper proposes a pre-processing technique named SRSSN relevant for Parkinson's detection. The performance analysis of the proposed technique has been evaluated using entropy, signal-to-noise ratio and contrast-to-noise ratio. The proposed technique performs better than the state-of-art techniques.

Keywords—*Parkinson's disease, Pre-processing, Magnetic Imaging Resonance, Quality enhancement.*

DOI Number: 10.14704/nq.2022.20.9.NQ44385 Neuro Quantology 2022; 20(9):3337-3347

I. INTRODUCTION

Parkinson's disease (PD) is a neurological disorder that leads to structural changes within the brain [1]. It is also responsible for the demise of dopamine-producing neurons inside the brain [2]. The scarcity of dopamine results in Parkinson's symptoms. It is a progressive disease where the symptoms tend to worsen over time. It starts with mild non-motor symptoms like fluctuating blood pressure, insomnia, anxiety, slowed responses, dizziness, headache etc. Hence, these are incapable of diagnosis [3]. By the time Parkinson's is discovered, the disease has already progressed. The progressive sign includes movement impairments like bradykinesia, tremor, seizures, balance disabilities, drooling etc. [4]. Parkinson's often occurs in older age. However, it may arise in individuals of any age. The detection test for Parkinson's are limited and are mostly subjective [5]. The neurologist detects it after the examination of visible signs along with the assessment of cognitive functions [6]. The medical history may play an important role in inspecting the cause of the disease. However, many times the cause is not found and hence, it is termed Atypical Parkinsonism [7]. Atypical Parkinsonism can be confirmed as Parkinson's after analysing the effect of the latter's medication namely levodopa. Levodopa can detect PD as the body responds to the drug only if it has Parkinson's.

The manual detection of PD may result in misclassification as the condition may be assumed as signs of the older age of drug-induced Parkinsonism [1]. Drug-induced Parkinsonism is a result of consumption of certain drugs like antipsychotics, antidepressants, calcium channel blockers etc. that leads to similar signs [8]. PD when misdiagnosed may progress and the signs may become critical and permanent. Hence, it is important to diagnose PD via some automated mechanism to reduce the misdiagnosis. Also, early detection is required as the disease may become more severe if not caught within time [9].

Nowadays researchers have been utilizing Magnetic Resonance Imaging (MRI) scans for its diagnosis [1]. However, pre-processing is a necessity as noise and artefacts may be introduced in the scans while acquisition [1]. Artefacts are irrelevant substances which can affect the anatomy thereby highly impacting the diagnostic capability of a classification model [10]. There are a variety of pre-processing techniques that may be applied to the scans. However, it is important to apply all the techniques necessary for improving the quality of the scans. Poor quality may result in inaccurate diagnostic results.

This paper proposes a fusion of pre-processing techniques named SRSSN that may help in improving the accuracy of Parkinson's detection. SRSSN is an abbreviation of Slice time correction, Realignment, Segmentation, Smoothening and Normalization. The work utilizes structural MRI (sMRI) scans as they can effectively monitor the structural changes within the human brain.

The objectives of this work are as follows:

1. To investigate the various pre-processing techniques utilized by the researchers relevant for PD detection via sMRI scans.
2. To propose a novel pre-processing technique for improving the MRI scans.
3. To perform a comparative analysis between the proposed technique and the state of art.

Performance analysis of the proposed pre-processing technique and the state of the art has been conducted via parameters like entropy, signal-to-noise ratio and contrast to noise ratio.

The paper has been organised as: Section 2 describes a literature review of existing pre-processing techniques. Section 3 presents the availability of the dataset. Section 4 describes the proposed work. Section 5 presents implementation and results. Section 6 presents performance evaluation and Section 7 concludes.

II. LITERATURE REVIEW

A review of the latest state of art techniques for Parkinson's detection has been performed and relevant information regarding the source of data, pre-processing steps, subject details etc. have been retrieved. The summary of the review is as follows:

Pahuja et. al. have suggested a multimodality PD detection technique based on T1 weighted sMRI scans and SPECT images [11]. An imbalanced dataset has been acquired from the PPMI database where 73 scans are of Parkinson's patients and 59 scans are of healthy ones. Pre-processing applied includes normalization, segmentation and smoothening. Features have been extracted from T1 weighted sMRI, SPECT scans and CSF. CNN has been used for performing classification. The technique achieved an accuracy of 93.33%.

Vyas et al. have presented a novel CNN-based Parkinson's detection framework on the PPMI database [12]. A total of 318 T1 weighted sMRI scans have been acquired. Authors have utilized bias field correction, histogram matching, normalization and image resizing for enhancing the MRI scans. 2D and 3D CNN have been applied where the latter outperformed with an accuracy of 88.9% and AUC of 0.86.

Gabriel et al. have suggested a T1 weighted sMRI-based Parkinson's classification technique [13]. An imbalance dataset of 330 diseased patients and 150 normal ones are extracted from the PPMI database. Realignment, segmentation, smoothening and co-registration have been performed by the authors. VBM has been performed to retrieve first order and second order features from gray matter. Out of seven different classifiers, SVM achieved maximum accuracy of 95%.

Khanna et. al. have proposed a pre-processing technique for improving the quality of T1 weighted MRI scans [14]. Dataset has been acquired from the PPMI database. The suggested technique is a combination of pre-processing techniques. It includes realignment, skull stripping, normalization and segmentation. An accuracy of 85%, the entropy of 0.79, CNR of 0.90

and SNR of 28.21 has been achieved by the authors.

A Parkinson's detection technique has been proposed by Chakraborty S. et al. [15]. Data has been retrieved from the PPMI database. The authors have performed spatial Normalization w.r.t. standard MNI template. However, the authors have not utilized any realignment for removing shape and size variability. Also, the author did not perform smoothening which is essential. An accuracy of 95.29% has been achieved.

Chen et. al. has proposed a structural MRI-based technique for classifying PD patients from healthy individuals [16]. Data has been retrieved from Beijing Tiantan Hospital, China. The authors have performed reconstruction and segmentation to enhance the quality of the dataset. Classification has been performed via SVM. The presented technique has attained an accuracy of 95%.

The authors have presented an optimized technique for classifying PD and Parkinsonism using FLAIR MRI [17]. T1 weighted sequence has been extracted from an unknown data source. SVM has been used for classification. An accuracy of 79% has been achieved.

Cigdem et. al. have introduced an SVM based PD diagnostic technique [18]. PPMI database has been explored for retrieving T1- weighted sMRI scans of 40 PD patients and 40 controls [11]. Pre-processing phase involves the conversion of Dicom to nifty, segmentation, normalization via the DARTEL method and smoothening. Features have been extracted from the 3D mask generated after performing VBM. SVM attained an accuracy of 90%. The authors have extracted a relatively smaller dataset.

Esmaeilzadeh et al. have suggested a CNN-based technique for classifying Parkinson's from healthy control [19]. The authors have retrieved T2 weighted sMRI scans along with SWI scans from the PPMI database. Data augmentation and skull stripping have been performed. CCN-based classification has been performed.

Zeng et al. have introduced a T1 weighted MRI-based technique PD [20]. A Dataset of 40 probable PD and 40 controls have been retrieved from an unknown source. The authors have applied segmentation and normalization w. r. t. DARTEL template and smoothening. Features have been extracted via VBM of gray matter and white matter regions. Classification has been performed via SVM and Leave-one-out cross-validation. Maximum accuracy of 95% has been achieved by the suggested approach.

Liu L. et. al. have presented a novel technique for Parkinson's diagnosis by utilizing T1 weighted sMRI scans [21]. Dataset has been acquired from the PPMI database. Skull stripping, removal of cerebellum and segmentation has been performed by the authors. Features have been extracted from gray matter and white matter regions. Regularized linear discriminant analysis (RLDA) has been utilized for performing classification. However, a lower accuracy of 70.5% has been observed.

Chen et al. have introduced a novel PD detection technique via an ensemble classifier based on SVM [22]. Parkinson's dataset has been acquired from the PPMI database and Alzheimer's data has been retrieved from OASIS. 3D scans are converted into 2D scans for reducing the complexity. Pre-processing techniques applied include averaging 3-4 scans of the same group, skull stripping, co-registration and bias field correction. Features have been extracted from the Scale-invariant feature transform (SIFT). An accuracy of 70% to 87% has been achieved.

A summary of related work has been presented in Table I.

TABLE I. SUMMARY OF REVIEW

S. No.	Authors	Pre-Processing Technique	Results
1.	Pahuja et. al., 2022 [11]	Normalization	An accuracy of 93.33 % has been achieved.
		Segmentation	
		Smoothening	
2.	Vyas et al., 2022 [12]	Bias field correction	3D CNN achieved an accuracy of 88.9%.
		Histogram matching	
		Normalization	
		Image resizing	
3.	Gabriel et al., 2021	Realignment	SVM achieved an accuracy of 95%
		Segmentation	
		Smoothening	

	[13]	Co-registration	
4.	Khanna et al., 2021 [14]	Realignment Skull stripping Normalization Segmentation	An accuracy of 85%, the entropy of 0.79 CNR of 0.90 and SNR of 28.21 has been achieved
5.	Chakraborty et al., 2020 [15]	Spatial normalization	The authors have achieved an accuracy of 95.29%.
6.	Chen et al. 2020 [16]	Reconstruction Volumetric segmentation	An accuracy of 95% has been achieved.
7.	Abos et. al., 2019 [17]	Removal of non-brain tissues Intensity normalization Co-registration	The proposed technique achieves an accuracy of 79%
8.	Cigdem et. al., 2018 [18]	Conversion of Dicom to nifty Segmentation Normalization Smoothening	The proposed technique achieves an accuracy of 90%
9.	Esmaeilzadeh et. al., 2018 [19]	Skull stripping Data augmentation	CNN achieved maximum accuracy.
10.	Zeng et. al., 2017 [20]	Segmentation Normalization Smoothening	Accuracy of 95% has been achieved.
11.	Liu L. et. al., 2016 [21]	Skull stripping Cerebellum removal Tissue segmentation	An accuracy of 70.5% has been observed.
12.	Chen et al. 2014 [22]	Averaging 3-4 scans of the same group Skull stripping Co-registration Bias field correction	An accuracy of 70% to 87% has been achieved

III. AVAILABILITY OF DATA

3D T1 weighted sMRI scans of diseased Parkinson's patients and healthy controls (HC) have been retrieved from the Parkinson's Progression Markers Initiative (PPMI) database (www.ppmi-info.org/access-dataspecimens/download-data). The scans have been acquired from Siemens Magnetization Prepared— Rapid Gradient Echo (MPRAGE) scans at 3 teslas for coronal, sagittal and axial planes. The time to echo and a repetition time of extracted dataset are 3ms and 827ms respectively.

The clinical information about the subjects is presented in Table II.

TABLE II. CLINICAL INFORMATION REGARDING HUMAN SUBJECTS

GROUP	PD	HC
Female/Male	40/45	34/49
Age Range	38-80	31-81

IV. PROPOSED WORK

This section presents the combination of pre-processing techniques essential for effective disease detection. Artefacts and noise must be removed to improve the quality of acquired scans [1]. The proposed technique comprises of pre-processing techniques namely Slice time correction, realignment, segmentation, smoothening and normalization. Thenceforth, this technique will be named as SRSSN in this work. Figure 1 presents the flow chart of the proposed pre-processing technique.

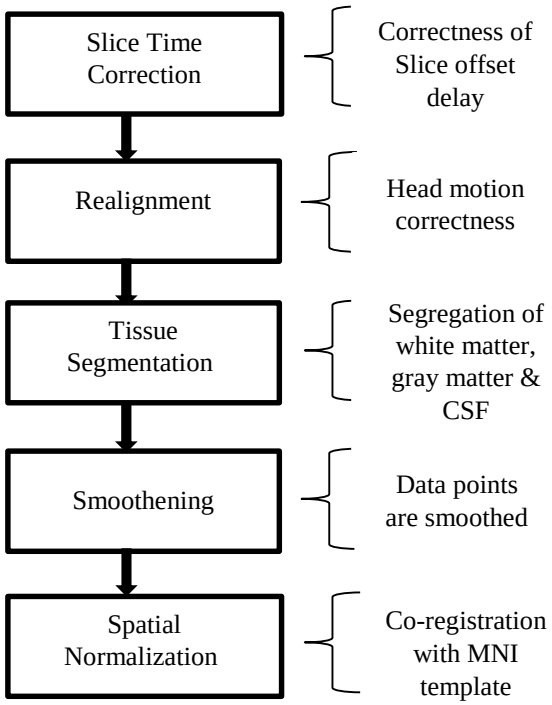


Fig. 1. Modalities for PD detection

1) *Slice time correction:* While MRI acquisition, it is possible that all the slices are not acquired instantaneously thereby resulting in offset delays between the first scan and subsequent scans [23]. Henceforth, slice time correction is performed to reduce the effect of slice delays. It may help in enhancing the performance of the model.

2) *Realignment:* Incorrect coordinates of data may be induced in MRI scans due to the Patient's head movement while acquisition thereby resulting in corrupted scans. Realignment is performed to reduce these variations of head movement [14]. It ensures that the brain is always in the same position. It is also referred to as head motion correctness. Realignment is capable of improving the results of segmentation and normalization.

3) *Tissue Segmentation:* Segregation of important brain tissues namely: gray matter, white matter and Cerebrospinal Fluid (CSF) is known as tissue segmentation [24]. Gray matter constitutes most of the central nervous system. It comprises the majority of cell bodies, dendrites and synapses. While the white matter is responsible for passing the messages to and from various gray matter regions. It comprises lesser cell bodies and more axons. CSF is a colourless fluid that acts as a cushion and prevents any damage to brain tissues.

4) *Smoothening:* Smoothening is performed to retrieve the original signal even in presence of noise [25]. The intensity of a pixel is replaced by the average of its neighbouring pixels.

5) *Spatial Normalization:* Human brain may vary in terms of shape and size [26]. Normalization refers to the co-registration of the subject's MRI with the standard human template to facilitate regional comparisons. In this work, co-registration has been performed via using a standard MNI template.

A. *Algorithm*

i. Slice time correction has been performed for all the extracted sMRI scans.

ii. Realignment is performed to facilitate head motion correctness.

iii. Segregation of white matter, gray matter and CSF has been conducted where only gray matter has been utilized. However, the rest are discarded.

iv. The segmented gray matter undergoes smoothening.

v. Co-registration of scans has been performed w.r.t. standard MNI template has been performed.

vi. The slice corrected, aligned, segmented, smoothed and normalized scans are used for performance analysis.

V. IMPLEMENTATION AND RESULTS

This section presents the implementation phase and results. The implementation of this work has been performed via SPM 12 within MatLab R2016b.

A. *Views of the Human brain*

A human brain has three views i.e. coronal view, sagittal view and axial view [30]. The coronal plane dissects the brain vertically i.e. into the back and front. The sagittal plane divides the human brain into left and right. The axial view splits the brain into the head and tail. Figure 2 represents the Coronal, Sagittal and Axial view of the T1-weighted MRI scan.

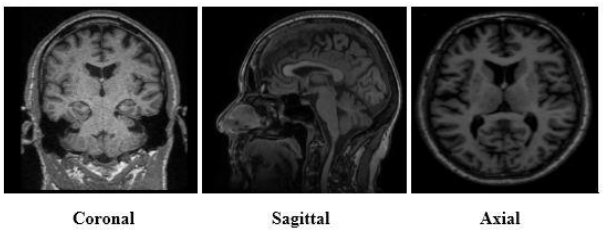


Fig. 2. Representation of three views of the human brain

B. Screenshots of the SRSSN

The order in which pre-processing steps have been applied are Slice time correction, realignment, segmentation, smoothening and Spatial Normalization.

i) Original scans of a subject

Original MRI scans of a subject are presented in Figure 3.

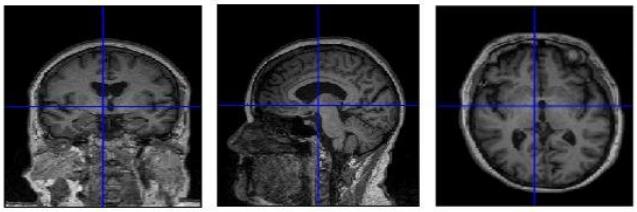


Fig. 3. Original MRI scan of a subject

ii) Slice time correction

MRI scans after slice time correction are presented in Figure 4.

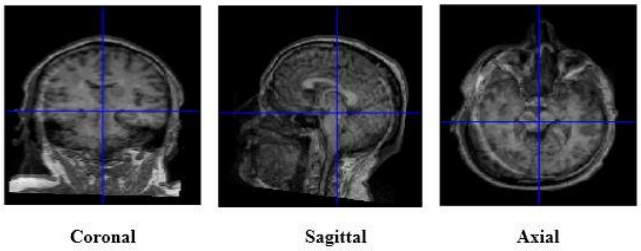


Fig. 4. MRI scan after slice time correction

iii) Realignment

MRI scans after applying realignment or head motion correction are presented in Figure 5.

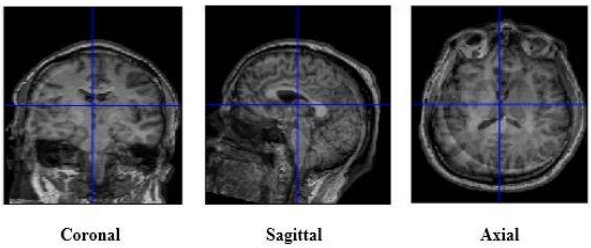


Fig. 5. MRI scan after realignment

iv) Tissue Segmentation

Segmentation of gray matter regions, white matter and CSF from the whole brain have been represented in Figure 6, Figure 7 and Figure 8 respectively.

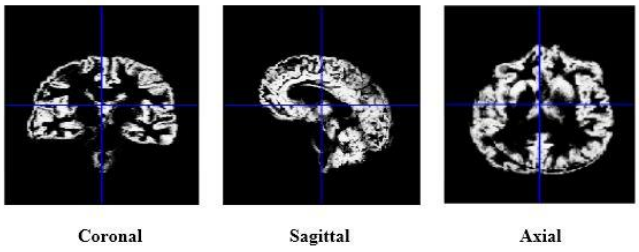


Fig. 6. Segmentation of gray matter from the whole brain

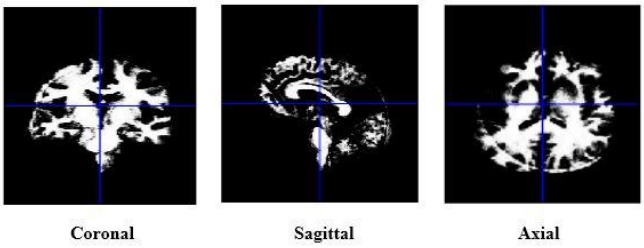


Fig. 7. Segmentation of gray matter from the whole brain

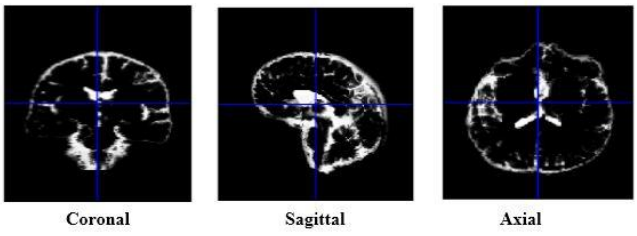


Fig. 8. Segmentation of white matter from the whole brain

v) Smoothening

Smoothening of segmented gray matter brain MRI scans is presented in Figure 9.

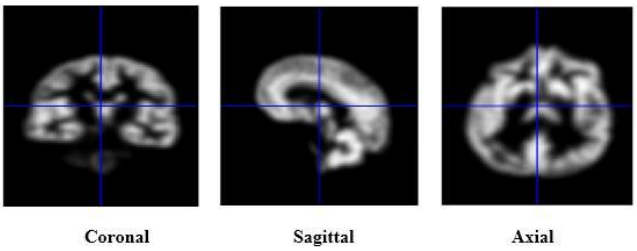


Fig. 9. Segmentation of CSF from the whole brain

vi) Spatial Normalization

Normalization of brain MRI according to the standard MNI template is presented in Figure 10.

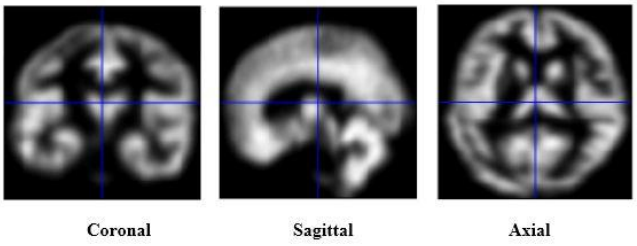


Fig. 10. MRI scans of gray matter after normalization

VI. PERFORMANCE EVALUATION

Due to the unavailability of required information for performance analysis of the state of art techniques, existing pre-processing techniques have been applied to the dataset retrieved from the PPMI database.

A. Performance evaluation parameters

Comparative analysis of the proposed technique and existing techniques has been performed via the following parameters:

i. **Entropy focus criterion (EFC):** It utilizes Shannon entropy of voxel intensities to determine head motion-induced blurriness [27].

The entropy function is a statistical property of images that measures the image information content [28]. The EFC can be computed as

$$\text{Entropy } (\lambda) = \sum_{n=1}^{S} [-P\left(\frac{B_j}{B_{max}}\right) * \ln(\frac{B_j}{B_{max}})] \quad (1)$$

Where

λ = Image Entropy

Bj= jth pixel's brightness

Bmax= largest possible pixel brightness if the image contained a single pixel. It can be calculated as-

$$\text{Bmax} = \sqrt{\sum_{j=1}^{S}(B_j)^2} \quad (2)$$

The greater the entropy of an image, the more smoothened and better that image is.

ii. **Contrast to Noise ratio (CNR):** It determines the contrast to noise ratio in a medical image [29]. It can be calculated as-

$$C = \frac{S_a - S_b}{\sigma} \quad (3)$$

Where

C = CNR

Sa, Sb = pixel intensities producing structures a and b

σ = standard deviation of pure image noise

The ratio of CNR must be high as lower values indicate more noise.

iii. **Signal to Noise Ratio (SNR):** SNR computes the ratio of true signal to noise [29]. Its formula is as follows-

$$\text{SNR} = \frac{\mu_a - \mu_b}{\sigma} \quad (4)$$

Where

μ_a= mean of Region of interest

μ_b = mean of the background

σ = standard deviation of the noise

A higher value of SNR describes more signal and lesser noise.

B. Comparative Analysis

This section presents the comparative analysis of the proposed technique and state-of-art techniques. Table III presents the performance analysis.

TABLE III. PERFORMANCE ANALYSIS

S. No.	Authors	Pre-Processing Technique	EFC	CNR (DB)	SNR (DB)
1.	Pahuja et. al., 2022	Normalization	0.63	0.55	18.28
		Segmentation			

	[11]	Smoothening			
2.	Vyas et al., 2022 [12]	Bias field correction Histogram matching Normalization Image resizing	0.59	0.45	19.20
3.	Gabriel et al., 2021 [13]	Realignment Segmentation Smoothening Co-registration	0.75	0.81	25.60
4.	Khanna et al., 2021 [14]	Realignment Skull stripping Normalization Segmentation	0.79	0.90	28.21
5.	Chakraborty et al., 2020 [15]	Spatial normalization	0.58	0.59	14.23
6.	Chen et al., 2020 [16]	Reconstruction Volumetric segmentation	0.55	0.42	13.09
7.	Abos et. al., 2019 [17]	Removal of non-brain tissues Intensity normalization Co-registration	0.61	0.53	20.72
8.	Cigdem et. al.,	Conversion of Dicom to nifty	0.64	0.67	22.24
	2018 [18]	Segmentation Normalization Smoothening			
9.	Esmaeilzadeh et. al., 2018 [19]	Skull stripping Data augmentation	0.71	0.81	24.51
10.	Zeng et. al., 2017 [20]	Segmentation Normalization Smoothening	0.62	0.68	21.93
11.	Liu L. et. al., 2016 [21]	Skull stripping Cerebellum removal Tissue segmentation	0.60	0.70	20.87
12.	Chen et al., 2014 [22]	Averaging 3-4 scans of the same group Skull stripping Co-registration Bias field correction	0.58	0.35	19.48
13.	**Proposed technique: SRSSN**	Slice time correction Realignment Segmentation	**0.92**	**0.96**	**29.74**

		Smoothening			
		Normalization			

Figure 11, 12, 13 presents graphical representations of the comparative analysis of Entropy, CNR and SNR respectively.

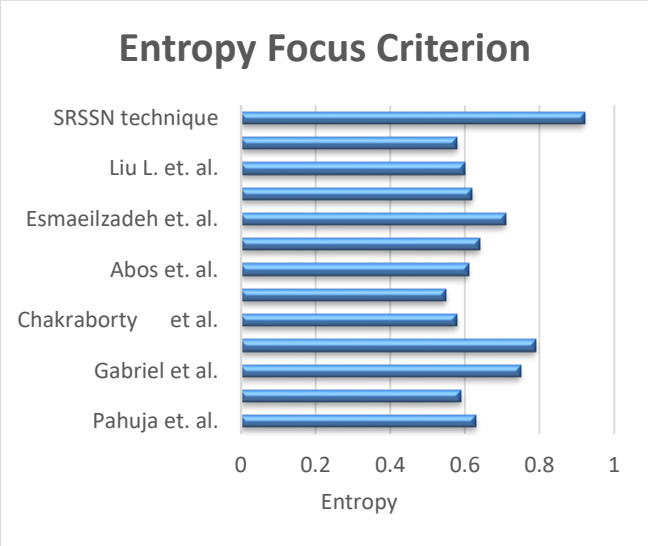


Fig. 11. Performance analysis w.r.t. Entropy

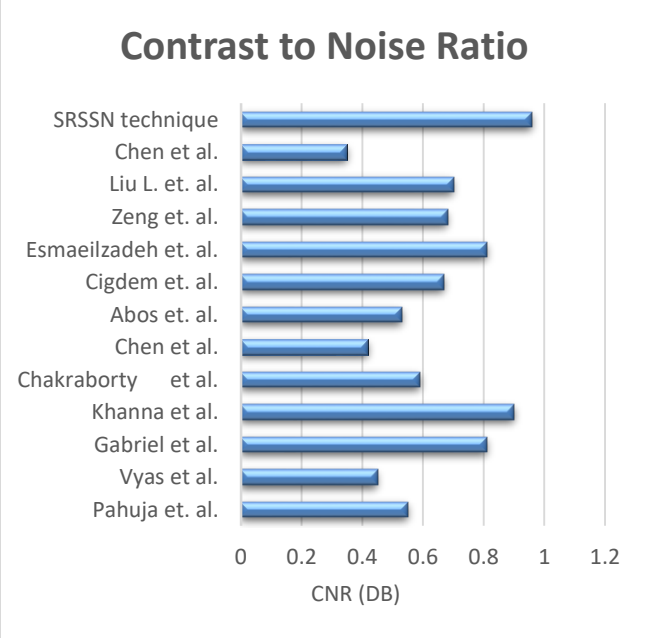
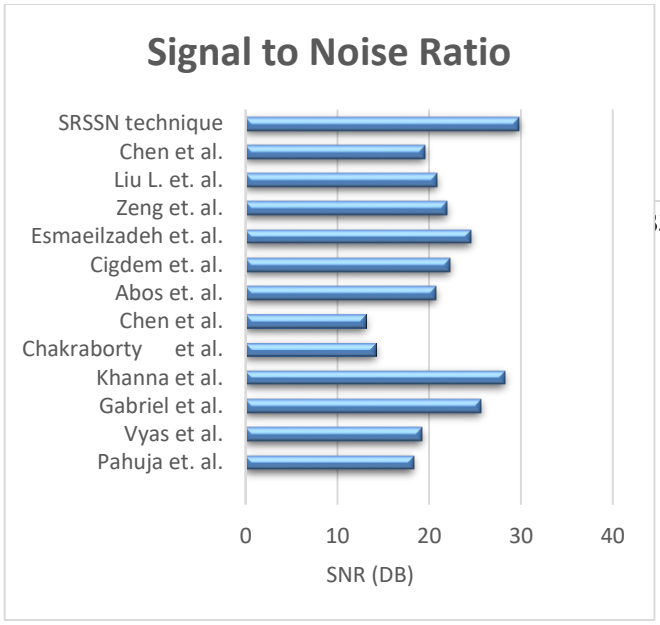


Fig. 12. Performance analysis w.r.t. CNR



.Fig. 13. Performance analysis w.r.t. SNR

Pre-processing is a vital phase that may help in improving the classification performance of a model. In this work, a novel pre-processing technique has been proposed for sMRI scans. From the results, it has been revealed that slice time correction, realignment, segmentation, smoothening and normalization are the best possible combination that significantly enhances the quality of MRI scans. From the results, it has been observed that the proposed technique performs better than the state-of-art techniques.

VII. CONCLUSION

Parkinson's is a degenerative disorder of the central nervous system. In this, the dopamine-producing neurons die that are responsible for message passing within the brain regions. The miscommunication results in motor and non-motor signs. The manual detection of PD may lead to a delay in detection. MRI-based Parkinson's detection may give promising results. However, the artefacts and noise present in MRI may severely impact the diagnosis and may change the anatomy. Hence, pre-processing is a dominant phase that may enhance the MRI scans thereby improving the diagnostic capability. The performance of the proposed technique SRSSN has been compared with state-of-art techniques via entropy, SNR ratio and contrast to noise ratio where the suggested technique outperformed. From the results, it has been observed that pre-

processing is a vital phase that must be performed before the Parkinson's diagnosis as it may help in enhancing the performance of a classification model.

Funding Information

PPMI a public–private partnership, is funded by the Michael J. Fox Foundation for Parkinson's Research and funding partners (see www.ppmi-info.org/fundingpartners).

REFERENCES

[1] K. Khanna, S. Gambhir and M. Gambhir, "Identification and Assessment of Pre-processing Techniques for Parkinson's Diagnosis," 2022 IEEE Delhi Section Conference (DELCON), 2022, pp. 1-4, doi: 10.1109/DELCON54057.2022.9753324.

[2] Tomer, S., Khanna, K., Gambhir, S., & Gambhir, M. (2022). Comparison Analysis of GLCM and PCA on Parkinson's Disease Using Structural MRI. International Journal of Information Retrieval Research (IJIRR), 12(1), 1-15. http://doi.org/10.4018/IJIRR.289577

[3] Tibar Houyam, El Bayad Khalil, Bouhouche Ahmed, Ait Ben Haddou El Hachmia, Benomar Ali, Yahyaoui Mohamed, Benazzouz Abdelhamid, Regragui Wafa, Non-Motor Symptoms of Parkinson's Disease and Their Impact on Quality of Life in a Cohort of Moroccan Patients, Frontiers in Neurology, VOL. 9, 2018, DOI=10.3389/fneur.2018.00170.

[4] Moustafa AA, Chakravarthy S, Phillips JR, Gupta A, Keri S, Polner B, Frank MJ, Jahanshahi M. Motor symptoms in Parkinson's disease: A unified framework. Neurosci Biobehav Rev. 2016 Sep;68:727-740. doi: 10.1016/j.neubiorev.2016.07.010. Epub 2016 Jul 12. PMID: 27422450.

[5] K. Khanna, S. Gambhir and Mohit Gambhir, "Current Challenges in Detection of Parkinson's Disease", Journal of Critical Reviews, vol. 7, no. 18, pp. 1461-1467, 2020.

[6] Massano J, Bhatia KP. Clinical approach to Parkinson's disease: features, diagnosis, and principles of management. Cold Spring Harb Perspect Med. 2012 Jun;2(6):a008870. doi: 10.1101/cshperspect.a008870. PMID: 22675666; PMCID: PMC3367535.

[7] McFarland NR. Diagnostic Approach to Atypical Parkinsonian Syndromes. Continuum (Minneap Minn). 2016 Aug;22(4 Movement Disorders):1117-42. PMID: 27495201; PMCID: PMC5567217.

[8] Shin HW, Chung SJ. Drug-induced parkinsonism. J Clin Neurol. 2012 Mar;8(1):15-21. doi: 10.3988/jcn.2012.8.1.15. Epub 2012 Mar 31. PMID: 22523509; PMCID: PMC3325428.

[9] Khanna Ketna, Gambhir Sapna & Gambhir, Mohit, "Modalities for Parkinson's detection: An Insight," *2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON)*, 2022, pp. 851-854, doi: 10.1109/COM-IT-CON54601.2022.9850775.

[10] Khanna Ketna, Gambhir Sapna & Gambhir, Mohit. A novel technique for image classification using short-time Fourier transform and local binary pattern. Multimed Tools Appl 81, 20705–20718 (2022). https://doi.org/10.1007/s11042-022-12671-z.

[11] Pahuja G., Prasad B. Deep learning architectures for Parkinson's disease detection by using multi-modal features, Computers in Biology and Medicine, Vol 146, 2022, https://doi.org/10.1016/j.compbiomed.2022.105610.

[12] Vyas T. et al., Deep learning-based scheme to diagnose Parkinson's disease, Expert Systems, 2021, https://doi.org/10.1111/exsy.12739

[13] Gabriel SL and Roberto RR (2021) Classification of PPMI MRI scans with voxel-based morphometry and machine learning to assist in the diagnosis of Parkinson's disease. Computer Methods and Programs in Biomedicine 198(105793).

[14] K. Khanna, S. Gambhir, M. Gambhir (2021). Enhancing the Quality of MRI scans in Parkinson's Detection. Design Engineering, 10307-10328. Retrieved from

http://www.thedesignengineering.com/index.php/DE/article/view/8147

[15] Chakraborty, S., Aich, S., & Kim, H. C. (2020). Detection of Parkinson's Disease from 3T T1 Weighted MRI Scans Using 3D Convolutional Neural Network. Diagnostics (Basel, Switzerland), 10(6): 402. https://doi.org/10.3390/diagnostics10060402

[16] Y. Chen, G. Zhu, D. Liu, Y. Liu, T. Yuan, X. Zhang, Y. Jiang, T. Du, J. Zhang (2020) The morphology of thalamic subnuclei in Parkinson's disease and the effects of machine learning on disease diagnosis and clinical evaluation. Journal of the Neurological Sciences.

[17] Abos, A., Baggio, H. C., Segura, B., Campabadal, A., Uribe, C., Giraldo, D. M (2019). Differentiation of multiple system atrophy from Parkinson's disease by structural connectivity derived from probabilistic tractography. Sci. Rep. 9:16488.

[18] Cigdem O and Demirel H (2019) The Performance of Local-Learning Based Clustering Feature Selection Method on the Diagnosis of Parkinson's Disease Using Structural MRI. IEEE.

[19] Esmaeilzadeh et al., 2018, End-to-End Parkinson Disease Diagnosis using Brain MR-Images by 3D-CNN, arXiv:1806.05233.

[20] Zeng, L. L. et al. Differentiating patients with Parkinson's disease from normal controls using gray matter in the cerebellum. Cerebellum 16, 151–157 (2017).

[21] Liu L, Wang Q, Adeli E, Zhang L, Zhang H, Shen D (2016) Feature selection based on iterative canonical correlation analysis for automatic diagnosis of Parkinson's disease. Med. Image Comput. Computer Assist. Interv. 9901: 1–8. doi: 10.1007/978-3-319-46723-8_1

[22] Chen Yang, Storrs J, Tan L, Mazlack LJ, Lee JH, Lu LJ (2014) Detecting brain structural changes as biomarker from magnetic resonance images using a local feature based SVM approach. J. Neurosci. Methods, 221, 22–31. doi: 10.1016/j.jneumeth.2013.09.001.

[23] Parker David B., Razlighi Qolamreza R., The Benefit of Slice Timing Correction in Common fMRI Preprocessing Pipelines, Frontiers in Neuroscience, 13, 2019 DOI=10.3389/fnins.2019.00821.

[24] Veluchamy, M., Subramani, B. Brain tissue segmentation for medical decision support systems. J Ambient Intell Human Comput 12, 1851–1868 (2021). https://doi.org/10.1007/s12652-020-02257-8.

[25] Huang F, Cheng H, Vijayakumar S. Gradient weighted smoothing for MRI intensity correction. Conf Proc IEEE Eng Med Biol Soc. 2005;2005:3016-9. doi: 10.1109/IEMBS.2005.1617109. PMID: 17282878.

[26] Russell T. Shinohara et al., Statistical normalization techniques for magnetic resonance imaging, NeuroImage: Clinical, Volume 6, 2014, 9-19.

[27] Atkinson D, Hill DL, Stoyle PN, Summers PE, Keevil SF (1997) Automatic correction of motion artifacts in magnetic resonance images using an entropy focus criterion. IEEE Trans Med Imaging, 16:6, 903-10.

[28] K. Khanna, N. Chauhan, Applicability of Genetic Algorithms in image segmentation, International Journal of Emerging Technologies and Innovative Research, vol. 6, issue 6, pp 106-110, 2019.

[29] Timischl, F (2015) The contrast-to-noise ratio for image quality evaluation in scanning electron microscopy. Scanning, 37: 1, 54–62.

[30] Park JS et. al. (2010) A proposal of new reference system for the standard axial, sagittal, coronal planes of brain based on the serially-sectioned images. Journal of Korean medical science, 25(1), 135–141.