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Advanced methodologies resolving dimensionality complications for autism neuroimaging dataset: a comprehensive guide for beginners

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ABSTRACT

Autism spectrum disorder (ASD) is gender biased neurodevelopmental condition consisting of a triad of physiological symptoms. Neural images and neurobiology of cognitive disorders are complex but provide significant information and accurate visualization of developmental changes. The diagnosis is time-consuming and necessitates sufficient evidence to distinguish the disorder from other concomitant diseases. The most recent area of interest for cognitive research is neuroimaging, which is used to study the disorder's impact, affected region, and functional connectivity between the regions of interest. The challenges in the domain are the availability of data, the modalities of data, the selection of the correct processing strategies, and the result assessment complications. The study employed machine learning (ML) methods to process the autism data in both structural and functional data formats collected from the autism brain imaging data exchange (ABIDE) consortium. A comparative analysis among image processing methodologies with both data formats was successfully implemented. The variations in the processing pipeline and the outputs strongly suggest an emerging need for 3D/4D images to visualize better, accurate feature extraction and classification. The study aims to support the researchers in identifying the correct image format for specific objectives and the ML techniques, such as Gaussian median filters, segmentation methodologies for 2D data, or a well-defined preprocessing pipeline for 3D data, to achieve reliable and generalized results.

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1. INTRODUCTION

Automated real-time object identification is crucial for accurate decision-making in numerous domains using multimedia data. Image processing is the most preferred method for object identification in various application fields, including academics, product development, e-commerce, and healthcare [1]. The core applications of image analysis are feature extraction, security and surveillance, image recognition, and medical image analysis. Image analysis tends to image enhancement for standard images (images other than medical scans) [2], but for the medical image data, there is a predefined process including enhancements and segmentation for accurate classification [3]. Processing complexity with medical images for segmentation, classification, and localization of regions of interest associated with an anomaly can be resolved by implementing artificial intelligence (AI) strategies [4], [5]. Neuroimages in brain science are vital in the current scenario of a higher prevalence rate of cognitive disorders. Neuroimaging study provides insight into the brain in two main aspects: structural and functional. The discipline of neuroimaging has been enhanced by neuroimaging techniques such as structural magnetic resonance imaging (sMRI) and functional magnetic resonance imaging (fMRI), which provide information in multiple forms. The high-resolution images are visually scannable and interpretable by experts but have not yet been explored thoroughly. Extensive use of neuroimages in multiple formats such as structural scan slices-2D and the functional scans for temporal studies -3D- need specific strategies to process the individual format. Neural images and neurobiology of cognitive disorders like autism spectrum disorder (ASD) is complex to understand but provide significant information and visualization of developmental variations. ASD is gender biased neurodevelopmental condition consisting of a triad of physiological symptoms: repetitive behavior, communication impairment-verbal/nonverbal, and social interaction. The heterogeneous nature and symptom comorbidity are the prime challenges to diagnosing ASD. AI with neuroimaging produced great results in various classification research works.

The imaging dataset collected from distinct sites and in different forms needs to be standardized and cleaned for further analysis for accurate and reliable results. The preprocessing pipeline for 2D and 3D images contains multiple steps. Hence, it is important to explore the difference in the process and understand the output quality measurement units for both formats. The challenges are addressed and explained to improve the quality of the image analysis results.

Various imaging modalities and formats need to be in a standard format to be implemented with AI strategies. Medical image processing with multidimensional image formats is complicated due to the additional information added as the additional dimension. The primary obstacles with multidimensional images are large volumes, data complexity, and spatial and temporal information that need advanced methods over traditional image processing methods. Another complication is the interpretation and correct analysis of large-volume data. An experimental analysis was performed on the structural and functional data collected for autism disorder. The data slices extracted from the scans as 2D images and the magnetic resonance imaging (MRI) as 3D and 4D format (time is the fourth dimension) are processed using various AI methods. The preprocessing pipeline for 2D images consists of filters, resizing, and resampling, and the 3D MRI preprocessed using realignment, reslicing, segmentation, normalization, and smoothing. The combination of two complicated fields, which are autism classification and multidimensionality of medical images, makes it more significant. A comparative analysis is presented to help the neuroimaging research select the preprocessing pipeline based on the data format for effective and reliable analysis.

2. DOMAIN STUDY

2.1. Autism spectrum disorder

High heterogeneity in clinical implications and underlying neurobiology of ASD is the prime reason for not yet achieving consistent biomarkers [6]. Identifying consistent biomarkers or specific patterns for classification as whole or subcategories of ASD using neuroimaging techniques is the main objective of current studies worldwide. The challenges with autism neuroimaging analysis and studies are a lack of dataset availability, heterogeneous nature of data as collected from multiple sources and sites, data complexity, and dimensionality. Autism imaging data is complex due to the detailed anatomical structures it contains. To elaborate on the complications in ASD diagnosis with AI tools, the characteristics and features are discussed in this session. Autism is a neurodevelopmental impairment. The associated behavioral and brain changes are subject to vary across various stages of age. Autism is frequently associated with other diseases such as attention deficit hyperactivity disorder (ADHD), intellectual disability, or anxiety problems [7], [8]. Atomizing the complicated connections between the comorbidities and their impact on brain structure require a huge dataset and expert systems [9]. Autism brain imaging data repositories are available globally, but very few are available on open-source platforms. To generalize the findings, sufficient data must be available to establish robust and reliable neuroimaging markers and perform more statistical analysis. To ensure the standardization and reproducibility of neuroimaging analysis, feature fusion from multimodal datasets such as structural and functional images is applied in recent autism diagnosis research; the structural images for morphometric features and functional images for functional connectivity and region of interest (ROI) analysis. A new multimodality fusion classification approach to explore the uniqueness of schizophrenia and ASD [10]. Due to the methodological variations in the processing pipelines, interpretation and clinical implementation of findings are yet to be achieved.

2.2. Neuroimaging

Medical images are essential for anatomical studies and helpful in disease diagnosis. The images collected from various source are sensitive to different types of quality attenuations known as noise. Some of the common noises are salt and pepper, Gaussian noise, speckle noise, poisson noise, and blurred noise removal and filtering techniques used in medical images [11]. Noise in the scans exists due to the mechanical issues, technical settings or patient related chages such as the subject's position, physiological artifacts, image quality, and protocols applied at the time of scanning [12]. Dimensionality and data volume are two of the major criteria that need to be considered when selecting suitable strategies to process neuroimages. Removing noise artefacts is an essential process for imaging datasets. It can be performed using external recordings–electrode arrays, shielding and grounding, or data-driven methods such as statistical filtering–Gaussian, filter, median filter, wiener filter implemented with machine learning (ML) methods [13]. To apply the data for developing computer added solutions, require to be converted into standard format. A single 3D scan consisting of hundreds of slices which in turn stored in digital form. The volumes are likely to be increased with the increase of count of scans, which is difficult to store and handle. Such voluminous data need more computational resources, storage capacity, and time. Medical images typically available in three-dimensional and four-dimensional (neuroimaging informatics technology initiative (NifTI)) format, that is, 3D scans with a time parameter. Algorithms need to account for spatial relationships, anatomical structures across slices, and temporal changes.

The preprocessing of 2D neuroimaging contains the methodology to perform data cleansing, enhancement, and interpretation. Some of the most common types of noise present in the images are Gaussian noise [14], salt-and-pepper noise, speckle noise, beam hardening artifacts, motion artifacts, and geometric distortions, in addition with some compression artifacts like blurring, blockiness, intensity variations due to magnetic effects. The noise exists in 3D images is similar to the 2D images but contains some additional types of noise, such as spike noise, susceptibility artifacts, and ghosting artifacts. Specific to fMRI images, patient movment variation, head motion artifact, and hardware limitations also cause image quality degradation. The artifacts need to be addressed carefully and processed correctly for consistent and reliable results. Spatial and temporal are the two types of MRI need to be processed for artefact removal. Some of the most common artifacts present in the NIfTI format are:
– Thermal noise (Gaussian noise) – random electric fluctuations within the scanner.
– Motion artifacts – blurring, ghosting, or misalignment due to patien movement.
– Physiological noise – periodic signal fluctuations due to cardiac pulsation and respiration.
– Scanner drift – low-frequency intensity in image due to magnetic field or sensitive over a time span.
– Susceptibility artifacts – geometric distortions and signal loss due to air tissue interfaces like sinuses.
– Partial volume effects – averaging the signal, reduction in contrast, and spatial resolution.
– Spike noise – sudden transient in the time series due to hardware issues.
– RF interference, gibbs ringing, chemical shift, gradient nonlinearities, and eddy current artifacts.

The 2D image is a set of pixels, whereas the 3D and 4D images are known as a set of voxels. Significant variation was observed in the artifacts and noises present in both image formats. JPEG images contain compression noise, and the NIfTI images consist of motion, physiological, and scanner-related inconsistencies. Normalization processes the JPEG images for intensity correction and NIfTI images for spatial and temporal corrections. Based on the difference in both image formats, the study presented some highly recommended methods to enhance the image quality, with experimental analysis and results.

2.3. Pre-processing

In medical imaging, 2D and 3D scans refer to different methods of capturing and visualizing medical images. The key differences between the scans are discussed in this section. First-image representation, where 2D images are flat images containing structural information in a single-plane form at the other hand a more comprehensive view of the anatomy or pathology scanned with the volume added as the third dimension, allowing visualization of structures in multiple planes, is known as a 3D image.

Pre-processing extracts detailed information to provide a better vision and interpretation of the imaging datasets [15]. The pre-processing pipeline for medical images contains predefined steps, including noise removal, artifact removal, contrast enhancement, registration, and spatial normalization. As discussed above, 3D images have additional and intense information in the voxel form, a pixel with volume. The significance of these images is in the higher resolution, detailed information, and more clarity and consistency. 3D images are expensive and complex due to mechanical requirements, machine size, expert supervision, and larger volumes. Data alignment to a single slice is easy, but a set of multiple slices scanned at different time intervals is complicated and needs to be monitored carefully. Data segmentation in JPEG images defines the ROI and helps in masking, but in NIfTI images, it is a tedious task because the images are segmented into five fundamental segments known as grey matter (GM), white matter (WM), cerebrospinal fluid (CSF), bone, and soft tissues. Segmentation is crucial to accurately achieving the ROI analysis. Normalization involves transforming the data images to template coordinates to compare the brain activities within a subject or a group of subjects in a common standard anatomical space. Smoothing is a blurring effect performed by applying a three-dimensional Gaussian kernel to the normalized images to increase the signal-to-noise-ratio (SNR) and adjust the spatial variability. The study performed all the preprocessing steps with the resting state functional magnetic resonance imaging (rs-fMRI) images to achieve noise free standanrdized form of data.

3. METHOD

This section consists of dataset description, the ML algorithms applied with 2D and 3D datasets for data cleaning, and quality measurements for quality analysis, and results after performing denoising. The two-dimensional data applied to the convolutional neural network (CNN) model before and after denoinsing, for classification and achieved higher accuracy with the denoised data. The preprocessing pipeline implemented with fMRI, achieved high contrast images and images segments for volumetric, surface based, and functional connectivity findings.

3.1. Dataset description

The dataset applied for the analysis is taken from autism brain imaging data exchange (ABIDE II), an open-source repository of neuroimaging scans in various modalities, and clinical findings and demographic facts collected from multi-site global collaboration to support the researchers [16]. Structural, functional, and diffusion are various modalities of MRI, where sMRI is used for T1-weighted (T1-W) and T2-weighted (T2-W) high-resolution spatial and static information. Diffusion tensor imaging (DTI) illustrates the WM fiber tract using two parameters: functional anisotropy and mean diffusivity. The data consists of 23 sMRI and rs-fMRI scans with a segregation of 13 (autism) and 10 (normal control); all the images are in NIfTI (4D) format. The jpg (2D) slices are extracted using Python (nibabel package) and stored as a 2D dataset.

3.2. Denoising

Two datasets were created using the jpg slices and blood oxygen level dependent (BOLD) data for analysis. The jpg provides the structural information, and the fMRI data provides physiological information and functional network attenuation-related features, which are useful for classification [17]. NIfTI is a preferred file format that consists of MRI scans with a header file and BOLD signals. The BOLD signals are extracted from the raw images and processed using the preprocessing pipeline, where each step refines the signals for denoising [18]. The process begins with slice-time correction, followed by realignment, registration, and segmentation into grey, WM, CSF, and normalization as the final step. High-quality brain images are essential to achieve high contrast and lower noise rates [19]. AI algorithms are equipped with the capacity to analyze the quality of an image, enhance the quality, and produce mathematical evidence for the classification of the given image.

An experimental analysis compared the image quality generated post-application of various filters and the related peak signal-to-noise ratio (PSNR) metric values [20]. The 2D images are processed with Python image processing packages such as OpenCV, scikit-image, NumPy, SciPy, Pillow, and TensorFlow. Two fundamental metrics, PSNR and SNR are applied for quality measurement in various image-based studies. SNR is calculated by dividing the signal's power by the noise's power, but it does not consider the human visual system. The image quality for this analysis is calculated PSNR. PSNR is a logarithmic measure calculated by taking the square root of the mean squared error between the original and reconstructed images; the metric is more accurate as it considers the human visual system. The mathematical expression for PSNR as in (1).

$$PSNR = 10 \times log_{10}\left(\frac{MAX_{VALUE}^2}{MSE}\right) \tag{1}$$

Where, $\mathrm{MAX_{VALUE}}$ is the maximum possible value for a pixel (255 for an 8-bit image); MSE is mean squared error between the original image and the reconstructed image. A PSNR of 30 dB or higher is considered good quality, and a PSNR of 40 dB or higher is considered excellent quality.

The NIfTI scans are processed with the CONN toolbox [21]. The process was assessed using statistical parametric mapping (SPM), check registration module, visual analysis using the overlay functions on the segmented images, and the denoising results were examined using the histogram quality control–functional connectivity (QC-FC) charts. The aim of study is to present a result-oriented denoising strategies to prepare the data for reliable and accurate classification of images.

3.3. Experimental analysis

Filters can be defined on the neighboring elements and used to observe the prominent features to discriminate the structure of the brain [22]. Table 1 is an empirical analysis of image quality measures for autistic brains when applied 2D images with specific filters. Each slice was deflated at an average rate of 5%

during the image conversion, and the header information could not be interpreted for the data. Figure 1 shows the output slices acquired after adding Gaussian noise to the images.

Table 1. An empirical analysis of various filters

Filters	Image before adding noise	Image after adding noise	.gif image
Gausian filter	20.00	22.0	33.58
Median filter	19.93	22.34	38.13

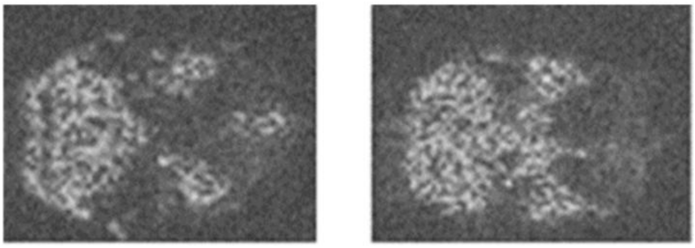

Figure 1. The sliced image scans of autistic brain MRI

The Gaussian and median filters are the most recommended for medical images applied for denoising [23]. Gaussian filter with different sizes of kernels, such as 3×3, 5×5, and 7×7, was applied as trial and test. The smaller kernel size produced maximum accuracy with higher processing time. The PSNR was calculated for the filtered images using a 5×5 kernel size. Figure 2, row 2, shows the filtered images without adding the noise, and row 3, after adding the noise. The images display the implemented filter and PSNR.

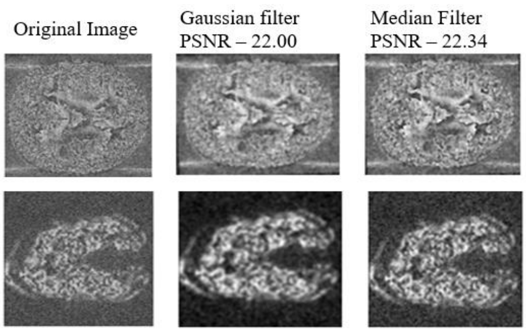

Figure 2. Denoised image slices of the brain MRI

Second, the image snapshots, taken from the dataset, were in .gif format. The visuals of the image are more evident than the sliced images. The median filter removes noise from the scans and preserves the WM-GM contrast at a larger scale for further analysis [24]. Several segmentation algorithms are available for segmentation and edge detection to divide the image into meaningful regions for further processing. The current work aims to denoise the images and, hence, the band-pass filters applied. Figure 3(a) displayed visual differences between original and filtered images and PSNR measures. The band-pass filter helps emphasize the edges and texture considered features, which are achieved by isolating the frequency range. Band-pass filters yielded better-quality images, where brain regions were segmented as edges and texture [25], as shown in Figure 3(b). However, it is seen that images are still noisy and may cause biased decisions. The denoising was performed successfully, and based on the SNR scale, results can be recommended for further analysis, such as segmentation, feature extraction, or classification.

The denoising performed on the other 3D format, recommending the 3D images for further analysis, depends on multiple preprocessing stages with specific parameters, such as realignment for motion correction, registration of all the slices belonging to the image to the origin (0 0 0), registration of the images to the standard Montreal Neurological Institute template (MNI) space, brain extraction by removing the nonbrain regions, segmentation, and smoothing [26]. The realignment results are stored as the regressors for quality analysis to accept and reject the images. The translation range for accepted scans was set to (<2 mm), and the rotation at (<0.5 degrees) and framewise displacement to choose the image with a significant rate of motion. Gaussian kernel with 8 mm full width at half maximum (FWHM) applied for smoothing; the kernel size varies–4 mm, 8 mm, and 12 mm for the hypothesis set. Figure 4(a) depicts the original image with the MNI template overlay, clearly showing that the image is noisy. Figure 4(b) is the resulting image preprocessed with the skull stripping, registration, and normalization.

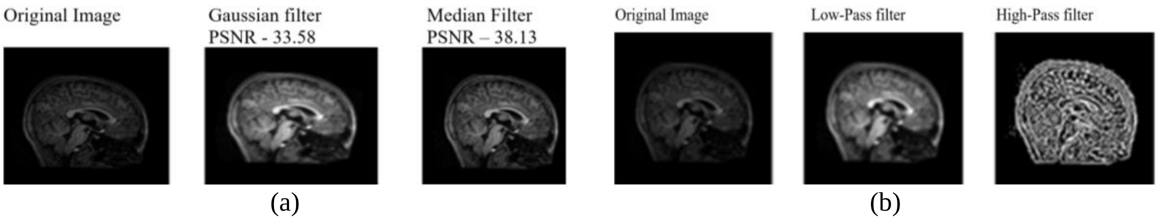

Figure 3. Filtered images using (a) Gaussian and median filters and (b) low-pass, high-pass filter

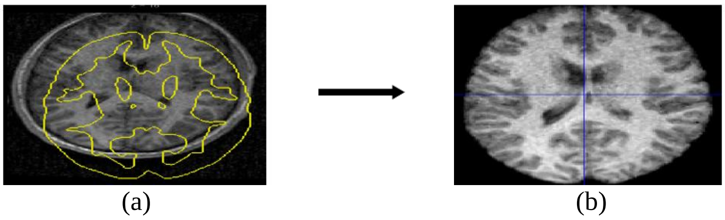

Figure 4. The NIfTI images (a) raw brain scan and (b) preprocessed brain scan

The resulting images in Figure 5 are the segmented images that help to explore each individual brain region to extract the values, coordinates, and volume of a voxel belonging to the particular region. In cognitive disorder research using neuroimaging, grey and whiter matter segments are considered significant regions of volumetric and surface-based analysis. The segmentation quality differs with the implementation of filters, Gaussian kernel provides better result for sMRI segmentations and volumetric analysis [27].

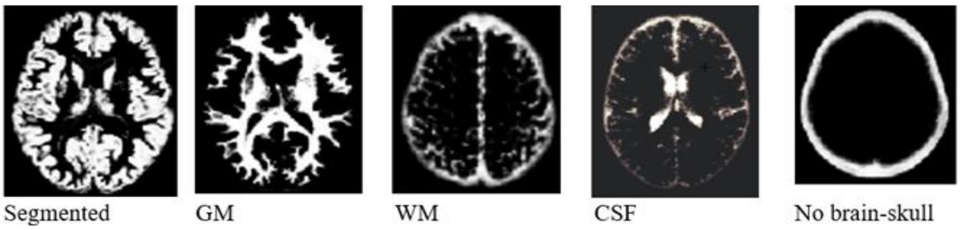

Figure 5. The segmented images into 5 basic tissue classes of brain

The physiological and motion signals in the scans need to be corrected for each voxel in time series extracted from the temporal data. Component correction (CompCor), and image transformation using rigid body transformation with 6-parameters (translation and rotation for x,y,z dimensions), 12-parameters (translation, rotation, scaling and shearing for x,y,z) applied for observing the impact of denoising [28]. After completion of the process, temporal artifacts are refined using bandpass filters. The time series extraction for temporal data is crucial. The data denoising was implemented using the Bandpass filters, with the range starting with 0.001 Hz and ending with 0.09 Hz using trial and error methods. The best results were achieved between 0.008 Hz for the high pass and 0.09 Hz for the low pass filter.

The denoising produces the results concerning functional connectivity analysis and needs to be assessed for noise effects on functional connectivity. The quality analysis scatter plot after denoising, in Figure 6, presents a relationship between the valid scans and the mean motion. The dots in the graph are the data points, the horizontal axis scale is valid scans, and the vertical axis scale is the MeanMotion measures. The quartiles depict the invalid scan. The plot is a quality analysis after denoising performed to check the effect of noise on the functional connectivity; the correlation between QC-FC is an artifact impact that should be flattened or minimized by denoising the current result, S1 depicts the outlier scan.

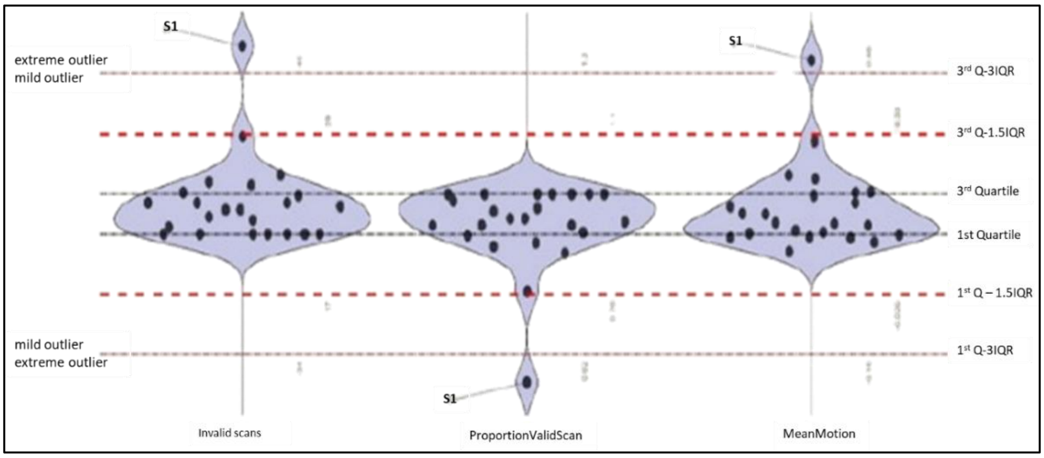

Figure 6. Quality analysis denoinsing: distribution of QC-FC association

The graph in Figure 7 shows the distribution of functional connectivity values before (the gray shaded area) and after denoising the yellow shaded area). Where all the twenty-three images are seen smoother after denoising, and the accuracy is observed as 88.4%. The next quality analysis performed on single images in the form of scatter plot, displayed in Figure 8 depicts the pre (the gray shaded area) and post-denoising (the yellow shaded area) effects on the connectivity measures, the deviations suggest the correction of noise.

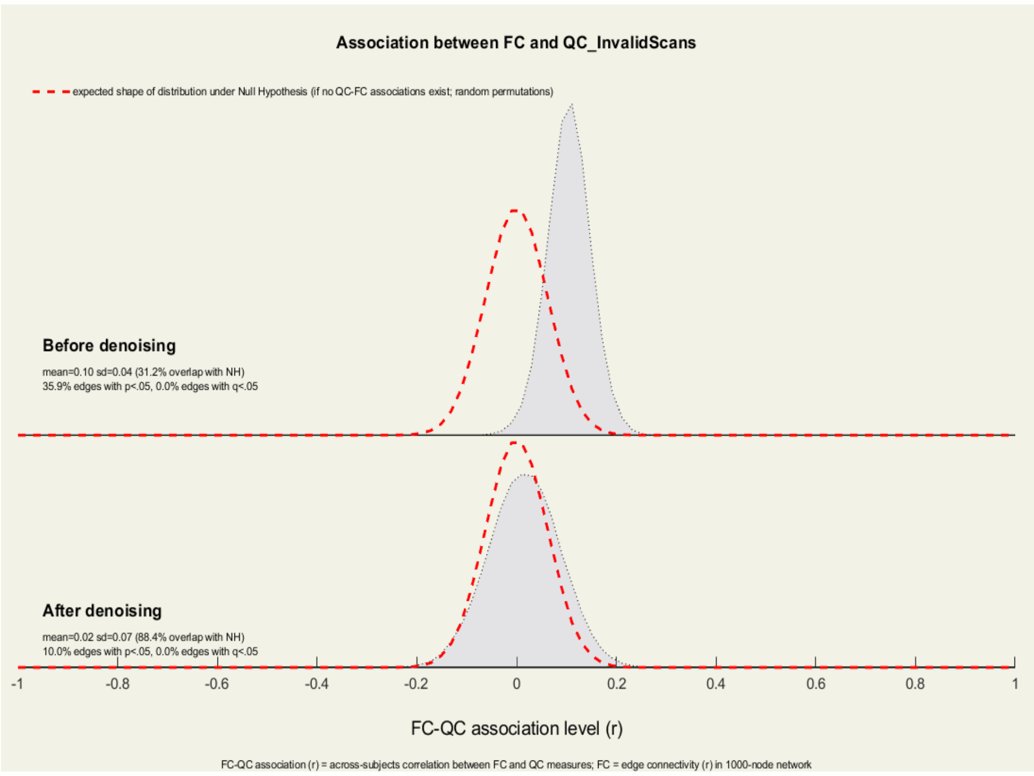

Figure 7. Quality analysis after denoising for the functional connectivity distribution (FC-QC)

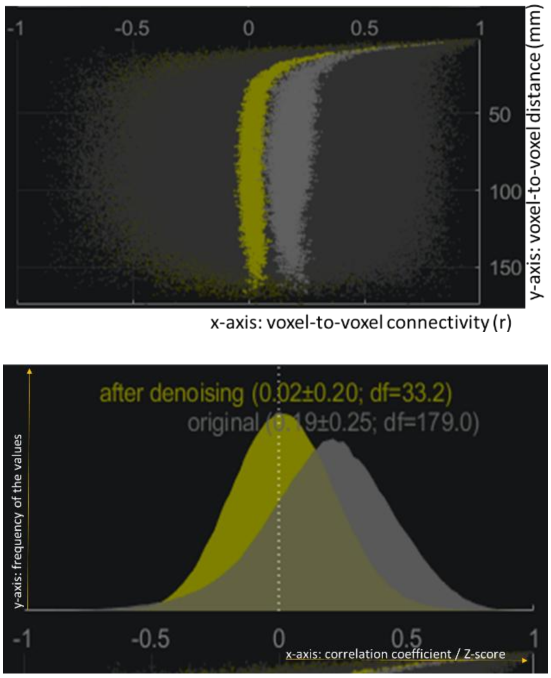

Figure 8. Voxel-wise distribution-scatter plot and histogram before and after denoising

The preprocessing results shown in the Figures 7 and 8, are the quality analysis results for jpg, gif, anatomic, and functional images. The results helps to eliminate the volumes that can effect the classification accuracy. Multiple tools are suggested for MRI processing in various neuroimaging research works, such as FMRIB Software Library (FSL), analysis of functional neuroimages (AFNI) [29], SPM [30], advanced normalization tools (ANTs), FreeSurfer [31], 3D slicer, neuroimaging in Python (NiPy), neuroimaging in Python-pipelines and interfaces (Nipype), and CONN for resting state and task-based connectivity analysis.

4. RESULTS AND DISCUSSION

Advancements in the automated classification model using medical images also require an update in the preprocessing pipeline. Although neuroimaging research in ASD produces a huge amount of information, it is challenging to achieve high-quality MRI images. The selection of the image processing pipeline is equally important as the selection of the correct imaging modality for accurate classification. The study presented modality-based denoising approaches to increase image quality. The denoising results proved that the jpg images are lossy and contain static information but are helpful for structure-based classification. The high-resolution 3D images are a source of temporal information, but the denoising is comparatively time-consuming and complicated, useful for event-based, resting state connectivity analysis such as cognitive disorders. Visual check and quality assurance parameters were observed successfully for both modalities. The MRI modalities are preferred for multiple cognitive disorder diagnosis using structural information, functional connectivity analysis, and the fusion of the features. Measurement consistency is crucial for parcellation and brain segmentation quality. Quality control ensures the detection of inaccuracies and correcting or excluding if required. The image quality for JPEG images was assessed using the CNN model with the raw images and filtered images; the classification rate was found to be higher after denoising. The functional images were applied for ROI analysis, and a significant difference in the connectivity measures before and after preprocessing was found. The study highlighted the neuroimaging modality variations and the appropriate denoising strategies to achieve reliable, generalized, and accurate classification. The study also emphasized the ROI analysis using the segmented images, which is crucial for future analysis. The work was implemented with a limited number of images and can be performed with a larger dataset. The study is not applied to medical images of injury or tumor, and we believe structural modalities are useful for such classification. The challenge for researchers currently consists of critical issues such as multisite and multimodal datasets, multiple tools and techniques, and the selection of preprocessing steps. The current study offers extensive comparative results, aiming to guide neuroimaging researchers in choosing suitable modalities and preprocessing for a particular problem.

5. CONCLUSION

Due to the complex interactions and comorbidities with other impairments, the information observed using imaging data needs to be standardized and generalized globally. Dealing with the complexity effectively and extracting significant information from these images requires advanced techniques and algorithms. The results observed using 2D image denoising motivated using 3D images in further research to improve the process and achieve more discriminative results. Clear and intense information is crucial to achieving higher accuracy, which is only possible with 3D images. The future work is to implement more images with AI methods to prove the importance of MRI images for cognitive research. The methodological improvement also depends on the quality and dimensionality of the dataset. We tried some autistic MRI images in the single-layer format and found that the images were not as visually clear as in the 3D format and did not execute well with the applied filters. The need for present AI methodologies is a huge, intense, and more informative dataset to produce computer-added solutions for disorders like autism. There exists a magnificent diversity in the functional connectivity in the brain, which directly correlates with the heterogeneous nature of autism. The study suggests MRI images produce extensive information for underlying disorders. To address the challenges of autism, collective efforts in data repository initiatives, quality control, and standard tools and methodology for analysis are required.

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