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IMPROVING IJA SKILLS OF AUTISTIC CHILDREN THROUGH MOOD PREDICTION USING DNCNN AND WAVELET TRANSFORM ALGORITHMS

M. SWEDHA[1], Dr. A. DEVENDRAN[2], Dr. VIJI VINOD[3] and Dr. RAJAVARMAN V.N[4]

[1] Research Scholar, Department of Computer Applications, Dr. M.G.R. Educational and Research Institute, Chennai, Tamil Nadu, India. Email: swetha23.magesh@gmail.com

[2, 3, 4]Professor, Department of Computer Applications, Dr. M.G.R. Educational and Research Institute, Chennai, Tamil Nadu, India.

Email: [2]devendran.alagasamy@gmail.com, [3]vijivino@gmail.com, [4]rajavarman.vn@drmgrdu.ac.in

Abstract

Autism spectrum disorders (ASD) are a group of neurodevelopmental conditions that are characterised by difficulties in social communication as well as repetitive or restricted behaviours and interests. Because autism spectrum disorder (ASD) is becoming more common, it is essential to diagnose patients with ASD in order to provide them with effective treatment and intervention, particularly during early childhood. In this paper, Deep Denoising Convolutional Neural Network (DnCNN) algorithm is used to predict the mood assessment of autistic children. Autism images help to predict the mood of autistic children. Additionally, Discrete Wavelet Transform (DWT) and Non-Decimated Wavelet Transform (NDWT) algorithms are used to filter the autism images for accurate prediction of autistic children behaviours. These algorithms predict the mood of autistic children through statistical value. The proposed algorithm Deep Denoising Convolutional Neural Network (DnCNN) algorithm gives high accuracy about 96%. These algorithms improve the initiation of joint attention (IJA) skills of autistic children.

Keywords: Autism Spectrum Disorders (ASD); Deep Denoising Convolutional Neural Network (DnCNN) Algorithm, Discrete Wavelet Transform (DWT); Non-Decimated Wavelet Transform (NDWT)

1. INTRODUCTION

Autism, also known as Autism Spectrum Disorder (ASD), is a neurodevelopmental disorder that affects communication, social interaction, and behavior. It is a spectrum disorder, meaning that it affects individuals in different ways and to varying degrees. Some people with autism have severe symptoms, while others have milder symptoms. Autism is typically diagnosed in early childhood, usually before the age of 3. Some of the early signs of autism include delays in speech and language development, difficulty with social interactions and eye contact, repetitive behaviors or routines, and an aversion to changes in routine. It is believed that autism is caused by a combination of genetic and environmental factors. Although there is no cure for autism, early intervention and therapy can greatly improve the outcome for people with autism. Treatment may include behavioral therapy, speech therapy, and educational support, among others. It is important to understand that people with autism are diverse and have their own unique strengths, abilities, and challenges. With the right support, many individuals with autism lead fulfilling and successful lives. The treatment of autism can vary greatly depending on the individual and the severity of their symptoms. However, there are several approaches that have been shown to be effective for many people with autism. Behavioral Therapy focuses

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on teaching social, communication, and behavior skills through repetition and reinforcement. Common approaches include Applied Behavior Analysis (ABA) and Verbal Behavior Therapy (VBT). Speech and Language Therapy helps people with autism improve their communication skills, including speaking, listening, and understanding language. Occupational Therapy helps individuals with autism improve their fine motor skills, hand-eye coordination, and overall ability to complete daily activities. Children with autism often benefit from specialized educational programs and support services, including individualized education plans (IEPs) and speech-language therapy in the classroom. Some individuals with autism may benefit from medication to manage symptoms such as anxiety, depression, or attention deficit hyperactivity disorder (ADHD).Some people with autism use alternative and complementary therapies, such as music therapy, massage therapy, and dietary changes. However, it is important to note that the effectiveness of these treatments is not well established. It is important to work with a healthcare professional to determine the best treatment approach for an individual with autism. A combination of different therapies may be necessary to achieve the best outcome. A mood assessment is a process used to evaluate an individual's emotional state or well-being. The purpose of a mood assessment is to identify any symptoms of depression, anxiety, or other mood disorders, and to determine the appropriate treatment. There are several methods for conducting a mood assessment. Self-Report Questionnaires method involves asking the individual to complete a written questionnaire about their emotions and symptoms. These can range from simple checklists to more assessments that are comprehensive. A mental health professional may conduct a clinical interview with the individual to gather information about their mood, thoughts, and behaviors. A mental health professional may observe the individual's behavior and interactions to gather information about their mood and emotional state. A physical examination may be performed to rule out any medical conditions that could be causing mood symptoms. Psychological testing, such as a depression inventory or anxiety scale, may be used to further evaluate the individual's mood and emotional state. It is important to remember that a mood assessment is just one-step in the process of identifying and treating a mood disorder. If a mood disorder is identified, a comprehensive treatment plan should be developed in collaboration with a mental health professional.

According to the Centers for Disease Control and Prevention (CDC), it is estimated that 1 in 54 children in the United States have been identified with autism spectrum disorder (ASD). This estimate is based on data from the CDC's Autism and Developmental Disabilities Monitoring Network and represents a significant increase from previous estimates. It is important to note that autism is a global issue, affecting individuals and families in countries around the world. The exact number of individuals affected by autism is not known, but it is estimated that it affects millions of people globally. It is also worth noting that autism affects individuals across all racial, ethnic, and socioeconomic groups. However, research has shown that some groups, such as boys, are diagnosed with autism more frequently than others. It is important for individuals with autism and their families to have access to appropriate services and support to help them lead fulfilling and successful lives.

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Problem statement

Autism is a neurodevelopmental condition that is part of a larger group of conditions that are collectively referred to as pervasive developmental disorders (PDD). These conditions are distinguished by three fundamental deficits: impaired communication, impaired reciprocal social interaction, and restricted, repetitive, and stereotypical patterns of behaviours or interests. Children who have autism spectrum disorder may have trouble developing language skills and others are saying comprehending what to them. They frequently struggle to communicate in other ways as well, including through hand gestures, eye contact, and facial expressions and expressions on their faces. To solve this problem Deep Denoising Convolutional Neural Network (DnCNN) algorithm is proposed through prediction of autistic children behaviours.

Contributions

In this paper, Deep Denoising Convolutional Neural Network (DnCNN) algorithm is proposed for autistic children interaction and improves their skills.

- To analyse the autism spectrum disorder (ASD) state through proposed algorithm Deep Denoising Convolutional Neural Network (DnCNN)
- To predict the autism children mental state through proposed algorithm Deep Denoising Convolutional Neural Network (DnCNN) by using autistic children thermal images
- To predict the statistical values of autistic children through Discrete Wavelet Transform (DWT); Non-Decimated Wavelet Transform (NDWT)

2. LITERATURE SURVEY

A neurodevelopment disorder called autism spectrum disorder (ASD) causes issues with social communication. Early ASD identification, symptom severity quantification, and treatment effectiveness evaluation could all be revolutionised by deep neural network (DNN) algorithms with the capacity to predict ASD severity in a sensitive and reliable manner **[1].**To assist kids with ASD in honing their initiation of joint attention (IJA) skills, create an immersive computer-mediated caregiver-child interaction (C3I) system. A carer is included in the teaching loop of C3I, a novel computerised intervention system that keeps the benefits of both human and computer-administered intervention **[2].** A self-contained, closed-loop mobile application that uses movie stimuli to draw the child's attention and elicit particular social and behavioural reactions. These responses are captured with the camera on the mobile device and are subsequently analysed using computer vision algorithms. Here, in addition to outlining this paradigm, we validate the system for assessing toddlers with and without ASD who were exposed to the application in terms of measuring engagement, name-call responses, and emotional reactions **[3].**Interactive activities like playing cooperative puzzle games can help ASD children develop their verbal and cooperative communication skills. During game play, the intelligent agent can also automatically assess how well kids perform verbal and cognitive tasks. To assess the viability and performance of the intelligent agent, two pilot studies

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involving kids with ASD were carried out **[4].**The current gold standard for diagnosis, in addition to expert clinical judgement, is the autism diagnostic observation schedule (ADOS). Currently, research focuses on creating machine learning and objective computer-aided technologies to diagnose autism. A discriminating image modality that assesses the functional activation of the brain is task-based fMRI. Despite the fact that autism is defined as a wide spectrum, computer-aided diagnosis systems aim to classify autistic subjects against typically developed peers**[5].**Atypical gaze behaviours related to joint attention, a crucial social-communication skill, are frequently seen in children with ASD. Children with ASD specifically display differences in gaze sharing and gaze following abilities. Children with ASD can play games on a cutting-edge virtual reality (VR) platform called InViRS that allows them to practise gaze sharing and gaze following. The ASC-Inclusion platform places a special emphasis on the bodily, vocal, and facial expression of emotion. The platform combines various analysis tools and makes use of the built-in webcam and microphone **[6-7].**Our network ablation analysis helped to shed light on the pathology of autism spectrum disorders and how the connectivity of networks that were crucial for categorization were associated with verbal communication deficits in autism. Neuroimaging-based diagnostic classification of mental disorders is improved through multi-site data harmonisation using ComBat. ComBat could increase the viability of AI-based clinical decision-support systems in psychiatry **[8].**As a result, many autistic people may experience daily difficulties, which occasionally manifest as depression, unemployment, or addiction. When compared to a control sample of typically developing people, participants from a participant sample of autistic people can be classified with high accuracy using machine learning techniques, proving the viability of the approach **[9].**ASD-related functional connectivity anomalies have been used to characterise complex biomarkers using neuroimaging techniques. a deep belief network (DBN)-based classification model that makes use of the Autism Brain Imaging Data Exchange (ABIDE) database, a global multisite aggregation of functional and structural brain imaging data used for ASD diagnosis**[10].**Our automated computer-aided diagnostic (CAD) system, which relies on the connectivity of the WM tracts to accurately identify autism spectrum disorder. Diffusion tensor imaging (DTI) data is used to provide two levels of analysis for local and global scores in order to accomplish this goal **[11].**To investigate whether eye-tracking data obtained from adults with and without high-functioning autism can be used to identify autism. As adults with and without autism browse through web pages in search of information, observe their eye movements. After that, train machine learning classifiers to recognise the condition using the recorded eye-tracking data **[12].** To find out if electroencephalography (EEG) metrics could be used to predict the severity of ASD symptoms. The EEG brain networks were built using a dataset that was made available to the public, and four different EEG metrics were computed. Following that, we statistically compared the variations in brain networks among ASD kids of varying severity **[13].**The behavioural variations among ASD subgroups are subtle and can be challenging experts to manually identify. A computational framework that can simulate the interlocutors' vocal and gestural actions, with their complex interdependencies recorded using a trainable interlocutor-modulated (IM) attention mechanism during dyadic clinical ADOS interviews**[14].**Using the Autism Brain Imaging Data Exchange (ABIDE) dataset, machine learning has been extensively used for multi-site autism classification**[15].**

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Inferences from Literature survey

There are different types of algorithms used to predict the mood of autistic children such as deep neural network (DNN) algorithm, machine learning, computer-aided diagnostic (CAD) system, deep belief network (DBN)-based classification model, virtual reality system and computer-mediated caregiver-child interaction (C3I) system. Computer-mediated caregiver-child interaction (C3I) system needs more time consuming, absence of regulating feedback and it lack of true human contact. Virtual reality is very expensive, complex technology and cannot move by our own like. Computer-aided diagnostic (CAD) system need large quantity of time and implementation cost is high. To solve this problem Deep Denoising Convolutional Neural Network (DnCNN) algorithm is proposed.

3. METHODOLOGY

Figure 1 shows the block diagram of Deep Denoising Convolutional Neural Network (DnCNN) algorithm for autistic children.

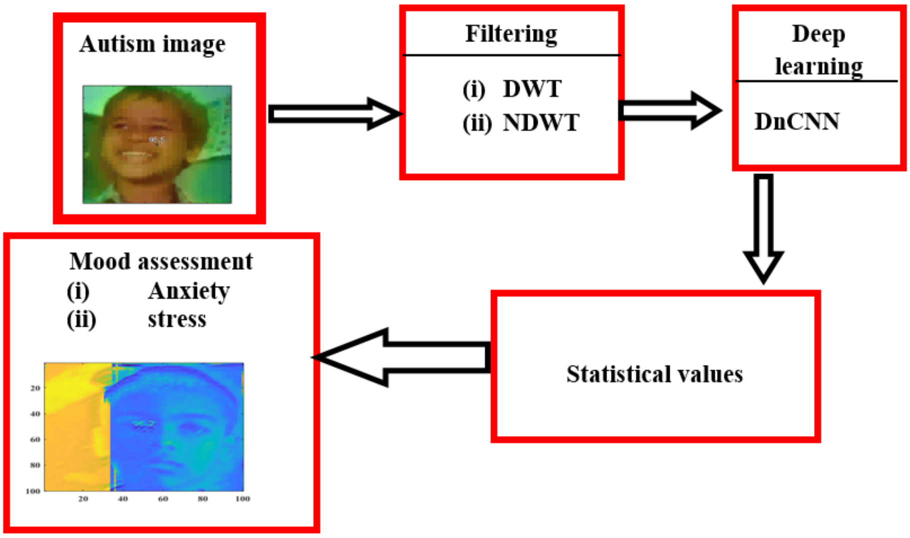

Fig 1: Block diagram

3.1. DWT

Discrete Wavelet Transform (DWT) is widely used in image processing for its ability to analyze an image into its constituent frequencies and provide a multi-resolution representation of the image. This is particularly useful in image compression, feature extraction, and denoising. In image processing, DWT is used to transform an image from the spatial domain into the frequency domain, where it can be analyzed for its different frequency components. This analysis can reveal important information about the structure and content of an image and can be used for a variety of purposes. For example, DWT can be used to identify and remove noise in an image, to extract features such as edges and corners, or to compress an image by

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removing less significant frequency components. One of the advantages of using DWT in image processing is that it provides a more flexible and localized analysis of an image compared to other frequency analysis techniques, such as the Fourier Transform. DWT allows for the analysis of different frequencies at different levels of detail, providing a better understanding of the underlying structure of an image and the ability to preserve important features even after compression.

Overall, DWT has become an important tool in image processing for its ability to analyze and manipulate images in a way that can reveal important information and improve the quality of the result. The equation for Discrete Wavelet Transform (DWT) in image processing involves transforming a 2-dimensional signal (such as an image) from the spatial domain into the frequency domain. The DWT is performed using a wavelet function and a series of convolutions and sub sampling operations. Let f(x, y) be a 2-dimensional image with dimensions M x N. The DWT of the image can be performed using the following steps:

- Filter the image along the horizontal direction using a low-pass filter, h(x), to produce a smoothed version of the image, s(x, y).
- Filter the image along the horizontal direction using a high-pass filter, g(x), to produce the detail coefficients, d(x, y).
- Subsample the smoothed image and detail coefficients along the vertical direction to obtain the sub-sampled images, s'(x, y) and d'(x, y).
- Repeat the above steps for the sub-sampled images along the vertical direction.

The resulting smoothed and detail coefficients are combined to form the 2-dimensional DWT of the image. The DWT coefficients can be used to represent the image in the frequency domain, where they can be analyzed and manipulated to reveal important information about the structure and content of the image.

In mathematical terms, the DWT equation can be expressed as follows:

$$S(x, y) = \sum\sum f(u, v)\, h(x-u)\, h(y-v) \quad \textbf{(1)}$$

$$d(x, y) = \sum\sum f(u, v)\, g(x-u)\, g(y-v) \quad \textbf{(2)}$$

Where h(x) and g(x) are the low-pass and high-pass filters, respectively, used in the DWT. The summations are taken over the range of values for u and v, which depend on the dimensions of the image.

3.2. NDWT

The Non-Decimated Wavelet Transform (NDWT) is a variant of the Discrete Wavelet Transform (DWT) in image processing that does not perform sub-sampling, unlike the standard DWT. In the standard DWT, the sub-sampling step is used to reduce the size of image, making the computation more efficient. However, sub-sampling can result in loss of information, making it difficult to accurately reconstruct the original image from the transformed image.

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The NDWT solves this problem by retaining all of the coefficients obtained during the wavelet transform, thus preserving the complete information content of image. This makes the NDWT particularly useful in applications where the complete information content of the image is important, such as in image and video processing. In the NDWT, the wavelet transform is performed by convolving the image with a wavelet function and computing the coefficients at each step. The resulting coefficients represent the relative importance of each component in the image, and the NDWT provides a multi-resolution representation of the image, showing both the high-accuracy and low-accuracy information in the image at different levels of detail.

The NDWT has been used in various applications in image processing, such as image denoising, compression, and feature extraction. It provides a more flexible and localized analysis of an image compared to other frequency analysis techniques, such as the Fourier Transform, and can provide a better understanding of the underlying structure of an image and the ability to preserve important features even after compression. Overall, the NDWT is an important tool in image processing for its ability to analyze and manipulate images in a way and can reveal important information and improve the quality of the result. The equation for the Non-Decimated Wavelet Transform (NDWT) of a 2-dimensional image x can be written as:

$$y(i, j) = \sum_{k=0}^{N-1} x(k) * \psi(2^j * k - i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\textbf{(3)}$$

Where $y(i, j)$ is the wavelet coefficient at position i and scale j, $x(k)$ is the original signal, $\psi(k)$ is the wavelet function, N is the length of the signal, and j is the scale factor.

For a 2-dimensional image, the NDWT can be performed with the wavelet transform being performed in both the horizontal and vertical directions. The wavelet transform can also be performed in higher dimensions, such as for multi-channel images or video.

3.3. DnCNN

The Deep Denoising Convolutional Neural Network (DnCNN) is a deep learning approach for image denoising. It is designed to remove noise from an image while preserving important image details and features. DnCNN uses Convolutional neural network architecture to learn the mapping from noisy images to clean images, making it a powerful tool for denoising. DnCNN consists of several Convolutional layers, followed by a batch normalization layer, and a ReLU activation function. The network is trained on pairs of noisy and clean images, with the objective of minimizing the reconstruction error between the network's output and the clean image. The network is trained to learn a non-linear mapping that transforms the noisy image into a clean image, and it can be used for denoising images corrupted by various types of noise, such as Gaussian noise, Salt and Pepper noise, and others.

The advantage of using a deep learning approach for image denoising is that the network can learn complex, non-linear relationships between the noisy and clean images, and it can handle different types of noise. Additionally, the network can be fine-tuned on specific types of noise to achieve even better results. DnCNN has been shown to achieve state-of-the-art results on various image denoising benchmarks and has been applied to various applications, such as

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medical image denoising, hyper spectral image denoising, and others. The DnCNN approach has also been extended to other image processing tasks, such as image super-resolution and deblurring. Overall, DnCNN is a powerful tool for image denoising, offering a flexible and effective solution for removing noise from images and preserving important image details. The equation for the Deep Denoising Convolutional Neural Network (DnCNN) in image processing can be represented as:

$$y = f(x) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(4)}$$

Where x is the noisy input image, y is the denoised output image, and f(x) represents the mapping function learned by the network.

The mapping function f(x) is neural network architecture, consisting of multiple Convolutional layers, batch normalization layers, and ReLU activation functions. The network is trained to minimize the reconstruction error between its output and the clean image, which can be represented mathematically as:

$$J = \|y - x_{clean}\|^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(5)}$$

Where x_clean is the clean image, y is the network's output, and J is the reconstruction error.

During training, the network's parameters are updated using gradient descent or another optimization algorithm to minimize the reconstruction error. Once trained, the network can be used for denoising by applying the mapping function f(x) to a noisy image. The network has learned a non-linear mapping from noisy images to clean images, and it can be used to remove noise from images while preserving important image details and features.

4. RESULT AND DISCUSSIONS

Autism thermal images are used to predict the behaviour and mood of autism children through different algorithms such DWT, NDWT and DnCNN**. Figure 2** shows the output of DWT algorithm for autism thermal image. Table 1 shows the statistical value of DWT algorithm for autism thermal images.

DWT algorithm processed autism thermal image (Sample 1-Anxiety)	**DWT algorithm processed autism thermal image (Sample 2-Happy)**
 **(a) Input image**	 **(b) Input image**

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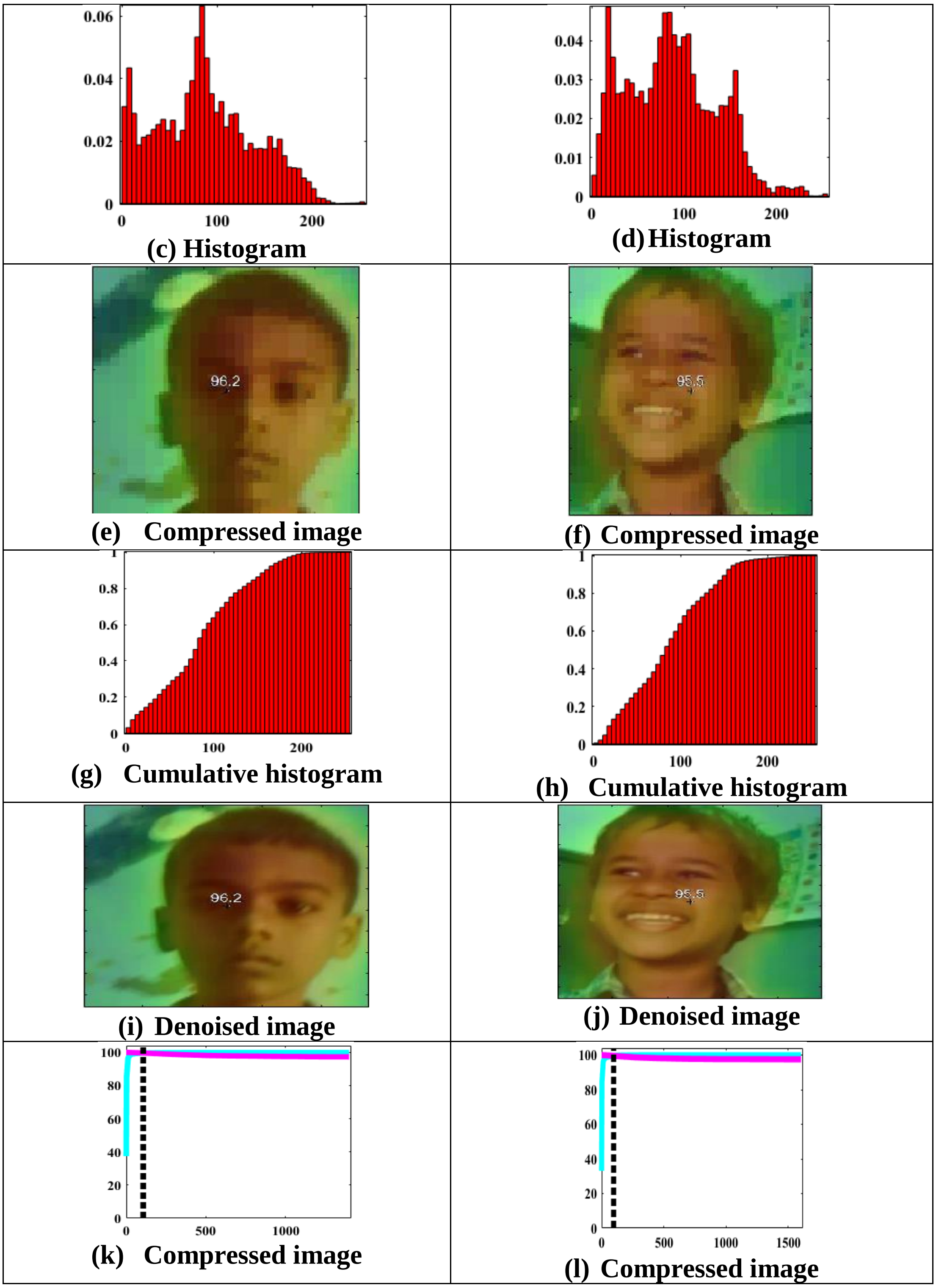

(c) Histogram

(d) Histogram

(e) Compressed image

(f) Compressed image

(g) Cumulative histogram

(h) Cumulative histogram

(i) Denoised image

(j) Denoised image

(k) Compressed image

(l) Compressed image

Fig 2: DWT algorithm processed autism thermal image

In the context of Discrete Wavelet Transform (DWT), denoised image refers to an image where noise has been reduced or removed using wavelet decomposition and thresholding. This involves decomposing the image into different frequency bands using DWT, identifying the noisy coefficients in the transform domain, and setting them to zero or applying a threshold to reduce their amplitude. The denoised image is obtained by applying the inverse DWT to the modified coefficients. A compressed image refers to an image that has been reduced in size through wavelet decomposition and quantization. This involves decomposing the image into different frequency bands using DWT, quantizing the coefficients in each band by rounding them to the nearest multiple of a quantization step, and discarding or storing only the significant quantized coefficients. The compressed image is obtained by applying the inverse DWT to the quantized coefficients. The degree of compression can be controlled by adjusting the quantization step or the threshold used for selecting significant coefficients. A histogram of wavelet coefficients is a graphical representation of the frequency of occurrence of different coefficient values in the wavelet domain of an image. It is obtained by counting the number of coefficients that fall within a certain range of values, and plotting the counts as a bar graph. The histogram can provide insights into the statistical properties of the wavelet coefficients and the underlying image, such as the level of detail or texture in different frequency bands, the presence of noise or artifacts, and the distribution of energy or power across different scales or resolutions. For example, a histogram that is skewed or has a long tail towards higher values may indicate the presence of outliers or significant coefficients that can be exploited for compression or denoising. Histogram-based techniques are often used in image compression and denoising with DWT, such as thresholding or quantization of the wavelet coefficients based on their statistical properties or perceptual relevance. The shape and characteristics of the histogram and the desired level of compression or fidelity can guide the choice of thresholding or quantization strategy. A cumulative histogram of wavelet coefficients is a graphical representation of the cumulative frequency of occurrence of different coefficient values in the wavelet domain of an image. It is obtained by sorting the absolute values of the wavelet coefficients in each subband or level of the DWT and computing the cumulative sum of the sorted coefficients. The cumulative histogram can be used to estimate the amount of compression or sparsity that can be achieved by retaining only a certain fraction of the largest coefficients, and discarding the rest. For example, the fraction of coefficients with values below a certain threshold corresponds to the fraction of energy or power that can be discarded while preserving a certain level of image quality or fidelity. The cumulative histogram can also be used to select appropriate thresholding or denoising strategies based on the statistical properties of the wavelet coefficients, such as their variance or distribution. In particular, the rate of change of the cumulative histogram can reveal whether a soft or hard thresholding approach is more appropriate, and whether a global or local thresholding strategy should be used.

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Table 1: statistical values of DWT algorithm

Parameters	Sample 1	Sample 2	Sample 3
Mean	87.5	86.8	85.58
Median	84	85	80
Maximum	255	255	255
Minimum	0	0	0
Range	255	255	255
Standard deviation	51.49	48.59	48.08
Median absolute deviation	37	37	37
Mean absolute deviation	41.6	39.65	40.67

In **Table 1**, mean, median, maximum, minimum, standard deviation range, median absolute deviation (MAD), and mean absolute deviation (MAD) are commonly used as statistical measures to describe the properties of an image. Mean value represents the average value of all the pixel intensities in the image. Sample 1 has high mean value about 81.5. Median represents the middle value of all the pixel intensities in the image. Sample 2 has the high median value about 85. Maximum value represents the highest pixel intensity value in the image. The highest value of maximum is 255. Minimum value represents the lowest pixel intensity value in the image. The lowest value of minimum is 0. Standard deviation refers a measure of the spread of the pixel intensity values around the mean. It indicates how much the pixel intensities deviate from the average. Sample 1 has high standard deviation about 51.49. Range refers the difference between the maximum and minimum pixel intensity values in the image. Median absolute deviation (MAD) refers a measure of the variability of the pixel intensities around the median. It is calculated as the median of the absolute differences between each pixel intensity value and the median of the image. Mean absolute deviation (MAD) refers a measure of the average deviation of the pixel intensities from the mean. It is calculated as the average of the absolute differences between each pixel intensity value and the mean of the image. The highest mean absolute deviation is 41.6. **Figure 3** shows the output of NDWT for autism thermal images.

NDWT algorithm processed autism thermal image (Sample 1-Anxiety)	**NDWT algorithm processed autism thermal image (Sample 2-Happy)**
 **(a) Compressed image**	 **(b) Compressed image**

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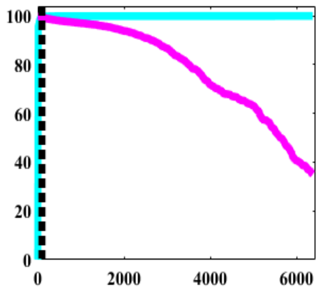
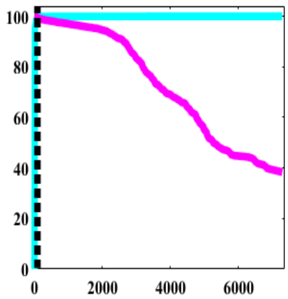


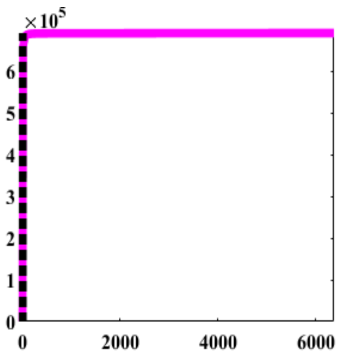
(c) compressed graph



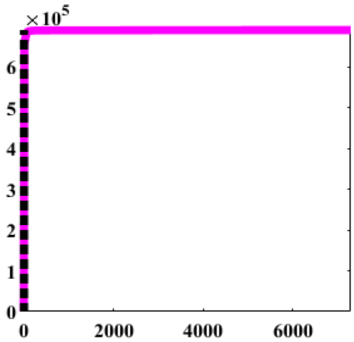
(d) compressed graph

(e) Denoised image

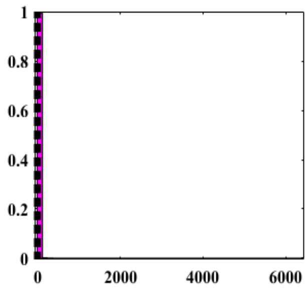
(f) Denoised image



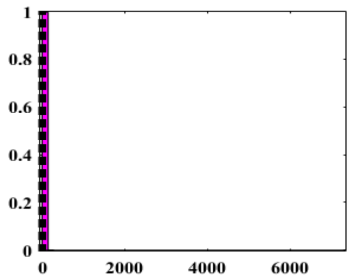
(g) Shorted absolute values of coefficients



(h) Shorted absolute values of coefficients



(i) Histogram of absolute values of coefficients



(j) Histogram of absolute values of coefficients

Fig 3: NDWT processed autism thermal images

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A compressed graph refers to a graph that is constructed based on a compressed version of an image obtained through wavelet decomposition and quantization. The compressed graph can be used for various tasks such as image retrieval, indexing, and classification. In particular, it can facilitate efficient and scalable processing of large image databases by reducing the size and complexity of the image representation, while preserving the discriminative and descriptive power of the original image. The compressed graph can be constructed by first applying NDWT and quantization to the image to obtain a compressed version, and then using the resulting wavelet coefficients as input to a graph construction algorithm. The graph can be constructed in various ways, such as by treating the wavelet coefficients as nodes and connecting them based on their similarity or distance, or by partitioning the wavelet coefficients into clusters and constructing a graph based on the relationships between the clusters. The compressed graph can be used for various tasks such as image retrieval, indexing, and classification, by applying graph-based algorithms such as clustering, classification, or ranking to the graph representation of the image. Sorting the absolute values of the wavelet coefficients is a common operation that can be used for various purposes, such as compression, denoising, feature extraction, and visualization. Sorting the absolute values of the wavelet coefficients means arranging the magnitude of the coefficients in a decreasing order. This can be done for all the coefficients in the wavelet domain or separately for the coefficients in each sub-band or level of the NDWT. The sorted coefficients can then be used to identify and discard the less significant coefficients or to retain only a certain fraction of the largest coefficients, as part of a thresholding or quantization strategy. Sorting the absolute values of the wavelet coefficients can also be used for feature extraction and visualization purposes. For example, the largest coefficients in the wavelet domain correspond to the most prominent edges or textures in the image, and can be used to generate a feature vector or image descriptor that captures the salient features of the image. The sorted coefficients can also be visualized as a curve or spectrum that shows the distribution of energy or power in the signal at different scales or resolutions. Overall, sorting the absolute values of the wavelet coefficients is a useful technique for various tasks in image processing with NDWT, such as compression, denoising, feature extraction, and visualization, and can help to improve the efficiency, accuracy, and interpretability of the image processing algorithms. The histogram of absolute values of coefficients can provide insights into the statistical properties of the wavelet coefficients and the underlying image, such as the level of detail or texture in different frequency bands, the presence of noise or artifacts, and the distribution of energy or power across different scales or resolutions. Furthermore, the histogram of absolute values of coefficients can be useful in visualizing the compression or denoising performance, by comparing the histograms of the original coefficients and the compressed or denoised coefficients. **Figure 4** shows the output of DnCNN for autism thermal images

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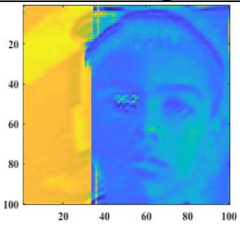
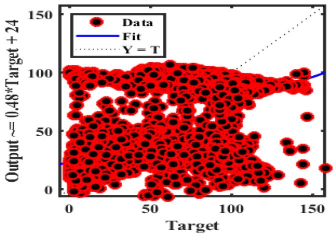
DnCNN algorithm processed autism thermal image

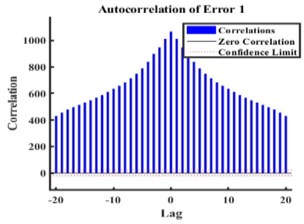
(a) Input image-Stress



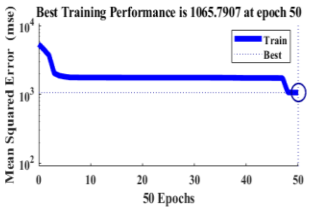
(b) Denoised image



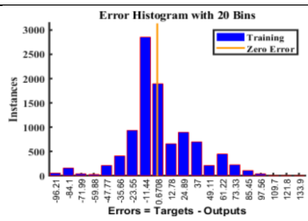
(c) Regression plot



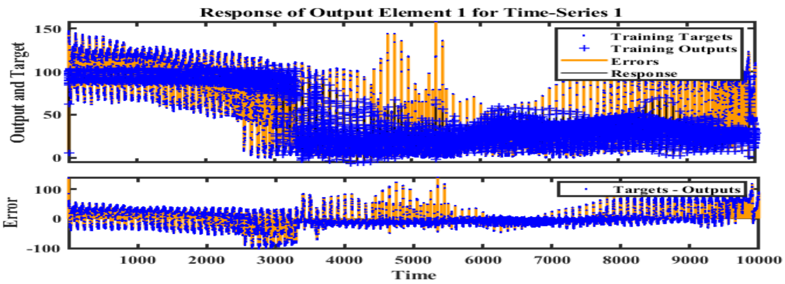
(d) Autocorrelation of error



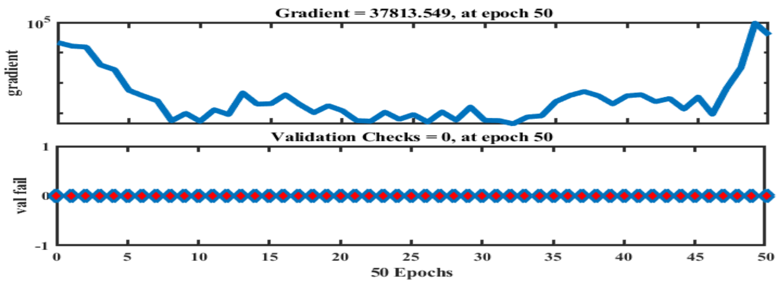
(e) Best training performance



(f) Error histogram



(g) Time series response



(h) Gradient, validation checks and epochs

Fig 4: DnCNN processed autism thermal images

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A regression plot is a graphical representation of the relationship between two variables in a dataset, often used in statistical analysis. In image processing, regression plots can be used to visualize the relationship between pixel values in two different images or between pixel values and an associated label or measurement. This can help identify patterns and correlations in the data, which can be useful for tasks such as image classification or object detection. Autocorrelation is a statistical measure of the similarity between an image and a shifted version of itself. Specifically, autocorrelation measures the correlation between a pixel and its neighbouring pixels at different distances and directions within the same image. Autocorrelation can be used to analyze the spatial frequency content of an image, which can be useful for tasks such as texture analysis or feature detection. High autocorrelation values at certain distances and directions may indicate the presence of repeating patterns or features in the image, while low autocorrelation values may indicate randomness or noise. Autocorrelation can also be used for image registration, which is the process of aligning two or more images that may have different orientations or translations. To generate an error histogram, the difference between the pixel values of the original and processed images is computed for each pixel, resulting in a new image that represents the errors. The histogram of this error image is then computed, which shows the distribution of the errors across different pixel values. The best training performance is achieved when an image processing model is trained to accurately and efficiently perform a specific task, such as image classification, segmentation, or object detection, on a given dataset. Time series response refers to the variation in image properties over time, often captured by a sequence of images acquired at different time points. Gradient, variation checks, and epochs are all related to the training process of an image-processing model. The gradient is used to optimize the model's parameters, variation checks are used to prevent over-fitting, and epochs determine the number of times the model is trained on the entire dataset. From the table 2 the DnCNN show high difference in statistical values compared to other algorithms

Table 2: Statistical values of NDWT/LBP/DnCNN algorithm

statistical values of NDWT algorithm			
Parameters	**Sample 1**	**Sample 2**	**Sample 3**
Mean	85.5	86.8	82.58
Median	83	85	79
Maximum	251	255	250
Range	242	255	250
Standard deviation	53.49	48.59	45.08
Median absolute deviation	31	37	39
Mean absolute deviation	041.6	39.65	40.67
statistical values of local binary patent (LBP) algorithm			
Mean	85.5	86.8	85.58
Median	86	85	85
Maximum	251	255	254
Range	253	255	254
Standard deviation	53.49	48.59	47.08
Median absolute deviation	35	37	38

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Mean absolute deviation	39.6	39.65	42.67
statistical values of DnCNN algorithm			
Mean	75.5	86.8	95.58
Median	79	90	95
Maximum	251	245	235
Range	245	225	215
Standard deviation	45.49	53.59	59.08
Median absolute deviation	25	37	47
Mean absolute deviation	35.6	39.65	45.67

5. CONCLUSION

Children diagnosed with ASD display a wide variety of symptoms, which can be quite dissimilar from one ASD case to another. These findings highlight the significance of choosing distinct training and testing samples when attempting to ascertain the robustness and consistency of performance. These features can be incorporated into a DnCNN model, which will result in a prediction of ADOS scores from autistic children that is astonishingly accurate. As a novel outcome measure for quantifying changes in ASD severity over time and in response to treatments, we propose that this analysis algorithm may have considerable clinical utility in determining early ASD risk. The proposed algorithm Deep Denoising Convolutional Neural Network (DnCNN) gives high accuracy about 96% during prediction of autistic children mood assessment.

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