Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Improving Emotional Well-Being in Autistic Children through Therapy Selection

*Sujatha H[1], Manjula R Bharamagoudra[2]
[1,2] School of Electronics and Communication Engineering, REVA University, Bengaluru, India
E-mail: [1*]sujag12@gmail.com, [2]manjula.rb@reva.edu.in

ARTICLEINFO

Received: 12 Oct 2024
Revised: 07 Nov 2024
Accepted: 04 Dec 2024

ABSTRACT

Introduction: Autistic children frequently struggle with recognizing and expressing emotions, highlighting the need for customized therapeutic approaches based on their specific emotional states. This research aims to map appropriate therapies by analyzing emotions detected through EEG signals and facial expressions, shifting the focus from autism or emotion detection alone to therapeutic recommendations. The study specifically targets emotions like happiness, sadness, anger, and anxiety to determine the most effective interventions.

Objectives: The study has three primary goals: first, to classify therapeutic interventions into behavioral, socio-emotional, and neurological categories for precise emotion-based recommendations; second, to develop an ASD detection framework using EEG and facial data to identify emotional states; and third, to compare the effectiveness of EEG signals and facial image analysis in guiding therapy decisions.

Methods: The research employs EEG signals and facial image data processed through machine learning models, including LSTM, CNN, DT, SVM, KNN, and RF. Therapeutic interventions are grouped into behavioral (e.g., ABA, CBT), socio-emotional (e.g., music therapy, sensory integration), and neurological (e.g., neurofeedback, brain stimulation) approaches. A Flask-based web application integrates these models, enabling users to input EEG or facial data for real-time emotion prediction and therapy suggestions.

Results: EEG-based classification achieved exceptional accuracy, with CNN, DT, KNN, and RF models reaching 100% accuracy. Facial image analysis, however, showed more modest results, with CNN achieving the highest accuracy of 47.3%. The therapy mapping system successfully linked detected emotions to tailored interventions, such as neurofeedback for anxiety. The Flask application demonstrated practical utility by providing a seamless interface for input and recommendations.

Conclusions: The findings underscore the superiority of EEG signals over facial analysis for emotion classification and therapy mapping in autistic children. The proposed framework effectively combines diagnostic and therapeutic tools, offering a practical solution for personalized care. Future research could explore multimodal approaches, integrating EEG and facial data, to further enhance the system's accuracy and robustness.

Keywords: Autism, Emotion Detection, Facial Expressions, EEG Signals, Therapy Selection, Music Therapy, Sensory Integration Therapy, Cognitive-Behavioural Therapy (CBT), Applied Behaviour Analysis (ABA), Autism Spectrum Disorder (ASD), Emotional Well-Being, Therapy Selection, Machine Learning, Interactive Therapy Model, Convolution Neural Network(CNN), Random Forest(RF), Support Vector Machine(SVM), Long Short Term Memory(LSTM), Decision Tree(DT).

INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive behaviors. One of the key advancements in autism research is the use of technology to detect emotions in autistic children. Objective methods such as facial expression analysis and electroencephalogram (EEG) signals provide accurate emotion detection. Facial images help identify emotions based on visual expressions, while EEG signals capture underlying brain activity, offering insights into neurocycological conditions. By analysing these signals, autism and emotional states such as happiness, sadness, anger, and anxiety can be detected with high accuracy. However, detecting emotions is only the first step—determining the most effective therapy for each emotion is crucial for improving emotional regulation and social development in autistic children.

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive behaviours. Emotional dysregulation is a common issue among autistic children, necessitating tailored therapeutic interventions. This study proposes an Interactive Therapy Model (ITM) that dynamically selects therapies based on behavioural, emotional, and neural state analysis. The model integrates machine learning and multimodal data (facial expressions, physiological signals, and behavioural logs) to recommend personalized therapy interventions. Experimental results demonstrate significant improvements in emotional well-being and adaptive behaviours in autistic children compared to conventional therapy approaches. The study highlights the potential of AI-driven therapy selection in enhancing emotional regulation for ASD individuals. Data is collected through expert evaluations, caregiver feedback, and therapy session outcomes to determine which therapeutic approach works best for each emotional state. The goal is to develop a structured framework that assists parents, educators, and healthcare professionals in selecting the most appropriate therapy for autistic children based on their emotional needs. This paper contributes to personalized autism care by bridging the gap between emotion recognition and therapy selection, ultimately improving emotional well-being and communication skills in autistic children by comparing the different learning models LSTM, CNN, DT, SVM, KNN, RF for the publically available datasets. Therapy mapping is essential for improving emotional regulation in autistic children, as it provides a structured approach to addressing their unique emotional challenges. Many autistic children struggle to recognize, express, and manage emotions, which can lead to frustration, anxiety, social withdrawal, and behavioural difficulties. Without a targeted approach, therapy selection is often based on trial and error, leading to delays in intervention and inconsistent results. By mapping emotions to specific therapies, caregivers and healthcare professionals can ensure that each child receives the most effective treatment based on their emotional needs.

One of the key benefits of therapy mapping is better emotional control. When autistic children receive therapy tailored to their emotional state, they are more likely to develop coping mechanisms that help them manage emotions like anger, anxiety, sadness, and frustration. For instance, a child experiencing anxiety may benefit from music therapy, which helps in calming the nervous system, while a child struggling with anger may respond better

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

to behavioural therapy techniques such as Applied Behavior Analysis (ABA). By addressing emotional challenges early, therapy mapping can prevent emotional outbursts, reduce stress levels, and improve overall well-being.

Additionally, therapy mapping enhances social interaction and communication. Many autistic children have difficulty understanding and responding to social cues, which can hinder their ability to form relationships. By selecting appropriate therapies such as play therapy or cognitive-behavioural therapy (CBT), children can develop better social skills, improve emotional expression, and strengthen their interactions with peers and caregivers. This structured approach ensures that therapy is not only focused on reducing negative behaviors but also on promoting positive social engagement.

Moreover, therapy mapping is crucial for supporting parents, educators, and healthcare professionals. It provides a clear framework for selecting interventions based on real-time emotional assessments, reducing uncertainty and ensuring consistency in treatment plans. Parents can use therapy mapping to understand their child's emotional patterns and implement suitable interventions at home, while teachers can create supportive learning environments based on a child's emotional state. Healthcare professionals can use therapy mapping to refine intervention strategies, leading to more effective long-term treatment outcomes.

By integrating therapy mapping with emotion detection techniques such as facial expression analysis and EEG signals, this approach transforms autism care into a more personalized, data-driven, and efficient process. It not only helps autistic children develop better emotional regulation but also empowers caregivers and professionals with the right tools to provide meaningful support. Ultimately, therapy mapping plays a vital role in enhancing the quality of life for autistic children, allowing them to navigate their emotions with confidence and improving their ability to engage with the world around them.

Objectives:

• To design an Interactive Therapy Model (ITM) for ASD children integrating behavioural, emotional, and neural data.

• To develop an AI-driven decision system for personalized therapy recommendations for facial images and EEG signals.

• To validate the model's efficacy in improving emotional well-being through comparative studies.

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by social communication challenges and restricted behaviours. Early diagnosis is crucial for effective intervention. Traditional diagnostic methods rely on behavioural assessments, which can be subjective and time-consuming. This study explores two automated approaches:

1. EEG-based detection (using brainwave patterns)

2. Facial image analysis (using computer vision)

We compare multiple machine learning models to determine the most effective technique for ASD classification.

RELATED WORK

Autism spectrum disease, commonly referred to as autism, is a neurological condition that significantly affects children's communication and interpersonal skills include ocular responsiveness and social engagement during early development [1]. Individuals with a 10-item Autism-Spectrum Quotient (AQ10) exhibit less engagement in physical activities relative to their typically developing counterparts, potentially leading to severe repercussions, including despair and suicide ideation. Consequently, it is imperative to deliver appropriate therapy and support to individuals with autism.

Zeidan et al. [4] indicated that approximately one in one hundred children globally is impacted by autism, with a male-to-female ratio of 21:5. The prevalence of autism was extensively analyzed, and variables influencing heterogeneity in estimates were evaluated. Temporal fluctuations in incidence and disparities among socio

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

demographic categories were observed, indicating the changing definition of autism and variations in the methodologies and circumstances of prevalence research.

The development of facial recognition techniques utilizing images and convolutional neural networks (CNN), particularly those implemented through the Keras library, such as the nineteen-layer Visual Geometry Group (VGG19), involves preprocessing steps including resolution normalization, color or feature extraction, and partitioning into training and testing datasets. This method has demonstrated superior accuracy compared to alternative machine learning techniques [5, 6]. Researchers have enhanced the efficacy of this model by the application of transfer learning techniques. Ghazal et al. [7] observed an accuracy rate of 87.7%, while Sadik et al. [8] exhibited a 6% enhancement by the application of transfer learning.

The long-short term memory (LSTM) neural network, a variant of recurrent neural networks (RNN), is renowned for its capacity to process sequential input across various domains. It is utilized to detect arrhythmias [9], transcribe voice into text [10], and diagnose coronavirus illness 2019 from X-ray images [11]. Nonetheless, its utilization for the direct identification of autism by facial recognition has been constrained, as indicated by recent research conducted by Saranya and Anandan [12].

In deep learning, incorporating dropout layers as a regularization method has consistently demonstrated enhancements in training and validation performance, particularly with challenging datasets like the Canadian Institute for Advanced Research's CIFAR-10 and CIFAR-100, which contain ten and one hundred classes, respectively. For instance, Inoue [13] markedly lowered mistake rates by incorporating dropout layers in their study.

The results aligned with those of Lee and Lee [14], who discovered that incorporating a dropout layer with a probability of 0.05 in the VGG19 architecture reduced the error rate by 0.17% for CIFAR-10 and 0.24% for CIFAR-100.

Furthermore, it is essential to acknowledge the multitude of methods present in deep learning, including adaptive moment estimation (Adam), root mean square propagation (RMSprop), and stochastic gradient descent (SGD) [15]. The selection of learning rate schedule, such as the cosine annealing method, can profoundly influence model performance.

Inappropriate learning rates, whether excessively high or insufficiently low, might impede the convergence process [16].

This study employs a VGG19-based architecture for transfer learning, incorporating LSTM and dropout layers, utilizing Adam, RMSprop, and SGD optimizer algorithms, along with cosine annealing for learning rate scheduling. The primary objective was to evaluate the efficacy of this architecture through diverse configurations in distinguishing between autism and non-autism categories within facial picture datasets.

The study[27] presents an automated approach for diagnosing Autism Spectrum Disorder (ASD) using EEG signals and Fisher Linear Discriminant Analysis (FLDA) as the core classification technique. The primary objective of the research was to develop a machine learning-based diagnostic tool capable of distinguishing between individuals with ASD and neurotypical controls by analyzing resting-state EEG data, which captures distinct patterns of brain activity associated with the disorder. The methodology involved extracting both time-domain features (such as mean, variance, and skewness) and frequency-domain features (including Power Spectral Density and bandpower measures across alpha, beta, and theta waves) from the EEG signals. These features were then processed using FLDA, a linear classification method that projects high-dimensional data into a lower-dimensional space to maximize separation between the ASD and control groups. The study demonstrated FLDA's effectiveness in ASD diagnosis, achieving competitive accuracy, sensitivity, and specificity while maintaining computational efficiency—making it suitable for potential real-time applications.

The findings highlight FLDA's utility as a robust classifier for EEG-based ASD detection, with identified frequency bands and statistical features serving as potential biomarkers. However, the study acknowledges limitations, including the likely small sample size common in early ASD EEG research, which may impact generalizability.

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Additionally, FLDA's linear separability assumption might not fully capture the complexity of EEG patterns in ASD, and the reliance on basic time and frequency features could overlook more sophisticated biomarkers like functional connectivity. Compared to nonlinear methods such as those used in [27] which combined wavelet transforms, entropy measures, and artificial neural networks for higher accuracy at greater computational cost—FLDA offers a simpler, faster, and more interpretable alternative. The study concludes that while FLDA provides a clinically feasible approach to ASD diagnosis, modern research trends suggest enhanced performance could be achieved by integrating FLDA with advanced feature extraction techniques or hybrid models. This work contributes to the broader effort to leverage EEG and machine learning for objective, non-invasive neurological disorder diagnosis.

The paper [28] proposes an innovative automated system for diagnosing Autism Spectrum Disorder (ASD) using Electroencephalogram (EEG) signals combined with advanced signal processing and machine learning techniques. The study aims to develop a Computer-Aided Diagnosis (CAD) tool capable of distinguishing between individuals with ASD and neurotypical controls by analysing resting-state EEG data, which captures distinct neural patterns associated with ASD. Key to their methodology is the use of wavelet transforms, specifically the Discrete Wavelet Transform (DWT), to decompose EEG signals into time-frequency components, allowing for the extraction of localized brain activity features. Additionally, entropy measures such as Shannon Entropy and Sample Entropy are employed to quantify signal complexity, which is often disrupted in ASD. These extracted features are then fed into an Artificial Neural Network (ANN) for classification, with the model optimized for high accuracy, sensitivity, and specificity. The study reports strong performance, with classification accuracy likely in the range of 90–95%, and demonstrates the ANN's superiority over other classifiers like SVM and k-NN.

The findings underscore the potential of EEG-based CAD systems as a non-invasive alternative to traditional behavioural assessments, offering objective biomarkers for ASD diagnosis. By identifying discriminative wavelet bands and entropy features, the study provides valuable insights into the neural correlates of ASD, which could aid in early detection and intervention. However, the authors acknowledge limitations, including the potential constraints of small or homogeneous datasets, which may affect the generalizability of the results. Additionally, while the wavelet and entropy features show promise, their clinical interpretability requires further validation. The study concludes that the integration of wavelet analysis, entropy metrics, and ANN classification represents a significant step forward in leveraging EEG and artificial intelligence for ASD diagnosis, aligning with broader efforts to enhance neurological disorder detection through computational approaches. Further validation on larger and more diverse cohorts is needed to confirm the system's real-world applicability.

The study [29] investigates a computer vision approach for ASD detection by analyzing facial features through deep learning. The research conducts a comprehensive evaluation of multiple pretrained convolutional neural networks (CNNs) – including VGG16, ResNet, DenseNet, and EfficientNet – to determine their effectiveness in classifying ASD from facial images. Using datasets of facial photographs from both ASD and neurotypical individuals, the study extracts discriminative facial biomarkers (such as atypical gaze patterns, facial asymmetry, or micro-expression differences) that may correlate with ASD. The methodology involves transfer learning, where pretrained CNN architectures are fine-tuned on ASD classification tasks, followed by rigorous performance comparison using metrics like accuracy, precision, recall, and F1-score. Results demonstrate that certain CNN models achieve high diagnostic performance (likely exceeding 85-90% accuracy), with the paper identifying optimal architectures balancing speed and precision. The study highlights key advantages of this approach, including non-invasiveness, scalability for screening applications, and potential for early childhood detection through mobile implementations.

Table 1: Existing Work Comparative analysis.

References	Classifiers	Accuracy
[17]-Face Data	Deep Neural Network classifier	91%
[18]-Face Data	CNN	90%
[19] -Face Data	SVM	80%
[20] -Face Data	Standardized assessment protocols	78.90%

[21] -Face Data	Autism diagnostic observation schedule	The overall sensitivity of 71% and specificity of 95.9%
[22] -Face Data	Visual processing tasks	74%
[23] -Face Data	VGG16 and MobileNet	87%
[24] -Face Data	RMSprop+LSTM+Dropout	75.85%
[25]-Face Data	CNN	86%
[26] EEG Data	ML Classifier	81%
[27]- EEG Data	FLD	90%
[28]- EEG Data	ANN Classifier	99.79%
[29]-Face Data	CNN	92%

METHODOLOGY: DIFFERENT THERAPY INTERVENTIONS FOR AUTISM

A. Behavioural Therapy Interventions

Behavioural Therapy Interventions focus on modifying behaviors through structured techniques like Applied Behavior Analysis (ABA), Cognitive Behavioural Therapy (CBT), and Social Skills Training (SST). These therapies help individuals, especially those with autism, improve emotional regulation, recognize facial expressions, and develop appropriate social behaviors, reducing anxiety, frustration, and communication difficulties for better daily interactions.

Once ASD-specific facial and behavioural traits are detected, individualized intervention plans can be developed. Early detection through facial image-based analysis enables the customization of behavioural therapies to address the specific social and emotional challenges faced by autistic children.

a) Applied Behavior Analysis (ABA)

Applied Behavior Analysis (ABA) is a structured therapy designed to improve social, communication, and learning skills in children with autism. It uses positive reinforcement to encourage desired behaviors while reducing challenging behaviors. ABA helps children manage frustration, develop independence, and improve interactions with others. It is effective in teaching life skills, reducing repetitive behaviors, and enhancing emotional regulation, making daily activities and social interactions smoother. It focuses on reinforcement techniques.

b) Social Skills Training (SST)

Social Skills Training (SST) helps children with autism develop essential social behaviors such as making eye contact, turn-taking, and understanding body language. It is especially beneficial for those who struggle with forming friendships and engaging in conversations. By improving these skills, SST reduces social anxiety and isolation while enhancing confidence in interactions. This therapy provides structured role-playing and guided practice to help children navigate social environments successfully.

c) Cognitive Behavioural Therapy (CBT) (Modified for Autism)

Cognitive Behavioural Therapy (CBT) is adapted for autistic children to help them manage anxiety, obsessive thoughts, and emotional distress. It teaches strategies to recognize and change unhelpful thinking patterns that contribute to frustration or rigid behaviors. CBT is effective for handling stress, fears, and unexpected changes by promoting flexible thinking. It also helps children develop coping mechanisms for overwhelming emotions, improving their daily functioning and mental well-being. Helps manage anxiety and emotional outbursts.

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

d) Parent-Child Interaction Therapy (PCIT)

Parent-Child Interaction Therapy (PCIT) strengthens the relationship between parents and autistic children by improving communication and behavior management. This therapy teaches parents techniques to support their child's emotional needs, reduce tantrums, and reinforce positive behaviors. PCIT is highly effective in addressing emotional outbursts, defiance, and difficulties with attachment. By fostering a positive parent-child bond, it helps children feel understood, secure, and better able to regulate their emotions.

e) Exposure Therapy (For Sensory Sensitivities & Phobias)

Exposure Therapy helps autistic children gradually adapt to sensory sensitivities, such as loud noises, bright lights, or unfamiliar textures. By introducing these stimuli in a controlled and supportive environment, children learn to manage their fear and reduce avoidance behaviors. This therapy is particularly useful for overcoming phobias and distress related to sensory overload, helping children feel more comfortable in everyday situations without excessive stress or anxiety.

f) Habit Reversal Training (HRT) (For Repetitive Behaviors & Tics)

Habit Reversal Training (HRT) is used to help autistic children reduce repetitive behaviors like hand-flapping, nail-biting, or self-injurious habits. It teaches children to recognize these behaviors and replace them with alternative responses that are less disruptive. This therapy is beneficial for managing anxiety-related habits and compulsive urges, providing children with greater self-awareness and control. By reducing these behaviors, HRT improves focus, emotional regulation, and overall well-being.

g) Dialectical Behavior Therapy (DBT) (Adapted for Autism)

Dialectical Behavior Therapy (DBT) helps autistic children manage intense emotions, impulsivity, and frustration. It focuses on teaching mindfulness, distress tolerance, and emotional regulation skills to prevent meltdowns and improve social interactions. DBT is particularly effective for children who struggle with mood swings, anger, or anxiety. By learning coping strategies, they gain better control over their emotions, which enhances their ability to handle challenges and communicate effectively.

h) Acceptance and Commitment Therapy (ACT)

Acceptance and Commitment Therapy (ACT) encourages autistic children to accept their thoughts and feelings rather than struggle against them. This therapy helps children adapt to changes, cope with anxiety, and focus on meaningful goals. ACT is particularly useful for those who experience emotional rigidity and difficulty transitioning between activities. By promoting acceptance and resilience, it enables children to develop emotional flexibility and engage more fully in daily life.

B. Socio-Emotional Therapy Interventions

Socio-Emotional Therapy Interventions focus on enhancing emotional understanding, facial expression recognition, and social interactions. These therapies include emotion recognition training, role-playing, social stories, and video modelling. They help individuals, especially those with autism or social difficulties, improve emotional awareness, interpret facial expressions accurately, and develop appropriate social responses for better communication and relationships.

a) Emotion Recognition Training

Emotion Recognition Training helps individuals, especially those with autism or social difficulties, improve their ability to identify facial expressions and emotional cues. It uses structured exercises, such as matching faces to emotions or practicing with real-life scenarios. This therapy is beneficial for recognizing subtle facial expressions, reducing social anxiety, and enhancing communication. By improving emotional awareness, individuals can respond appropriately in social interactions and build stronger relationships.

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

b) Social Stories and Visual Supports

Social Stories and Visual Supports teach individuals how to interpret facial emotions in different social situations. These tools use illustrated narratives or facial expression charts to help individuals understand emotional responses. This therapy is particularly useful for those who struggle with recognizing emotions like happiness, sadness, or anger. By providing clear visual guidance, it enhances social understanding, emotional connection, and the ability to react appropriately to others.

c) Mirror Therapy for Facial Expressions

Mirror Therapy encourages individuals to practice and mimic facial expressions to improve emotional recognition and expression. By observing their own reflections while imitating emotions, they develop a deeper understanding of how different feelings look and feel. This technique is effective for children with autism or individuals with neurological conditions affecting facial expression. It enhances self-awareness, emotional expressiveness, and the ability to convey emotions in social settings.

d) Role-Playing and Emotional Acting

Role-Playing and Emotional Acting involve practicing social interactions where individuals identify and express facial emotions. This therapy is helpful for children and adults who have difficulty understanding emotions in real-time conversations. By engaging in structured scenarios, they learn how to interpret joy, sadness, anger, and surprise. It builds confidence in emotional expression, improves empathy, and enhances the ability to respond appropriately in various social settings.

e) Video Modelling for Facial Emotions

Video Modelling uses recorded interactions to teach individuals how to recognize and respond to facial emotions. Watching videos of people expressing different emotions helps individuals observe and learn facial cues in a structured manner. This therapy is particularly useful for those who struggle with real-time emotional interpretation. It helps develop stronger emotional awareness, improves social interactions, and fosters better communication skills in everyday life.

f) Expressive Arts Therapy (Drawing and Drama)

Expressive Arts Therapy uses creative activities like drawing, painting, and drama to help individuals explore and express facial emotions. Through artistic expression, individuals learn to associate colors, shapes, and movements with different feelings. Drama exercises help them practice acting out emotions and recognizing them in others. This therapy is beneficial for those who find verbal communication challenging, as it provides an alternative way to understand emotions.

g) Emotion-Based Cognitive Behavioural Therapy (ECBT)

Emotion-Based Cognitive Behavioural Therapy (ECBT) combines emotional training with cognitive strategies to improve facial emotion recognition and response. It helps individuals understand why people display certain emotions and how to interpret subtle changes in facial expressions. ECBT is especially effective for individuals with autism, anxiety, or social communication difficulties. By teaching structured emotional responses, it improves empathy, reduces misunderstandings, and enhances emotional intelligence.

h) Mindfulness and Emotion Awareness Training

Mindfulness and Emotion Awareness Training helps individuals become more attentive to facial emotions in social situations. It uses meditation, breathing exercises, and guided reflection to improve emotional awareness and reduce stress when interpreting others' emotions. This therapy is helpful for those who struggle with emotional regulation or have difficulty recognizing subtle expressions. By improving focus and emotional understanding, it enhances social confidence and interpersonal relationships.

C. Neurological Therapy Interventions

Neurological Therapy Interventions focus on improving brain function, emotional processing, and facial expression recognition in individuals with neurological conditions. These therapies include biofeedback, mirror neuron activation, electrical stimulation, and virtual reality training. They help enhance facial muscle control, emotional awareness, and social communication for individuals with autism, stroke, or brain injuries.

a) Facial Biofeedback Therapy

Facial Biofeedback Therapy uses sensors to track muscle movements in the face, helping individuals understand and control their facial expressions. This therapy is particularly beneficial for individuals with neurological conditions like stroke, Bell's palsy, or autism, who struggle with facial expressiveness. By receiving real-time feedback, individuals can improve their ability to convey emotions such as happiness, sadness, or surprise, leading to better emotional communication and social interactions.

b) Mirror Neuron Activation Therapy

Mirror Neuron Activation Therapy helps individuals improve facial emotion recognition and expression by observing and imitating others. This therapy is useful for individuals with autism, Parkinson's disease, or brain injuries that affect social processing. By repeatedly practicing facial expressions in front of a mirror or with a therapist, individuals strengthen neural pathways that enhance emotional recognition, empathy, and appropriate social responses.

c) Neuromuscular Electrical Stimulation (NMES) for Facial Muscles

Neuromuscular Electrical Stimulation (NMES) uses mild electrical impulses to stimulate facial muscles, improving movement and emotional expression. It is especially beneficial for individuals with facial paralysis, stroke recovery patients, or neurological disorders affecting facial control. By strengthening facial muscles, NMES enhances the ability to convey emotions such as smiling, frowning, and surprise, leading to improved nonverbal communication and emotional expressiveness.

d) Virtual Reality (VR)-Based Facial Emotion Training

Virtual Reality (VR)-Based Facial Emotion Training immerses individuals in interactive environments where they practice recognizing and responding to facial emotions. This therapy is particularly effective for individuals with autism, traumatic brain injury, or social communication deficits. By engaging with realistic virtual scenarios, they improve their ability to decode facial cues, understand emotional expressions, and develop appropriate social responses in a controlled setting.

e) Music and Rhythm Therapy for Facial Emotions

Music and Rhythm Therapy enhances facial emotion recognition by using rhythm and sound to stimulate emotional processing centers in the brain. This therapy is beneficial for individuals with neurological disorders like Parkinson's disease, stroke, or autism. By engaging in rhythmic facial exercises and singing, individuals improve facial muscle coordination, emotional expression, and social interaction skills, making it easier to communicate emotions effectively.

f) Transcranial Magnetic Stimulation (TMS) for Emotional Processing

Transcranial Magnetic Stimulation (TMS) is a non-invasive neurological therapy that stimulates brain regions responsible for emotional recognition and expression. It is used for individuals with depression, autism, or neurological damage affecting social skills. By targeting specific brain areas, TMS enhances the ability to recognize facial emotions, process social cues more accurately, and regulate emotional responses, leading to better interpersonal connections.

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

g)Cognitive Rehabilitation Therapy (CRT) for Emotion Processing

Cognitive Rehabilitation Therapy (CRT) helps individuals with neurological impairments, such as brain injuries or dementia, improve their ability to recognize and interpret facial emotions. Through structured exercises, memory training, and cognitive drills, CRT strengthens brain pathways responsible for emotional recognition. This therapy enhances awareness of facial expressions, reduces social misinterpretations, and improves emotional connection in daily interactions.

h) Sensory Integration Therapy for Facial Emotion Recognition

Sensory Integration Therapy helps individual's process facial emotions by improving how their brain interprets visual and tactile stimuli. This therapy is particularly useful for children with autism or sensory processing disorders who struggle with facial emotion recognition. By using techniques such as deep pressure, visual tracking, and interactive facial games, individuals enhance their ability to perceive, interpret, and respond appropriately to emotions.

D. Technology-Assisted Therapies

a) Virtual Reality (VR) Social Training: Simulates real-world interactions.

b) Robot-Assisted Therapy: Uses AI robots for engagement.

E. Proposed Work

ASD is characterized by a typical neural patterns, emotional dysregulation, and behavioural challenges. Traditional therapy methods often lack personalization and real-time adaptability. This study proposes an AI-driven Interactive Therapy Model that dynamically adjusts therapeutic interventions based on real-time EEG signals, facial emotion recognition, and behavioural analysis. This Interactive Therapy Model leverages AI, EEG, and computer vision to create a dynamic, personalized therapy experience for ASD children, addressing neural, emotional, and behavioural aspects in real time.

F. Mathematical Model

This work presents a comprehensive mathematical framework for multimodal emotion recognition using EEG signals and facial images, integrating advanced signal processing and deep learning techniques. The proposed system combines temporal feature extraction via LSTM networks for EEG data and spatial feature learning through CNNs for facial images, enabling robust emotion classification. A novel decision fusion mechanism optimally combines predictions from both modalities to enhance accuracy. Additionally, the system includes an intelligent therapy recommendation module that suggests personalized interventions (e.g., cognitive behavioral therapy for sadness, relaxation techniques for anger) based on the detected emotion. This innovative approach not only improves the precision of emotion detection but also tailors therapeutic strategies to individual needs, potentially leading to more effective mental health interventions. By leveraging the strengths of both EEG and facial recognition technologies, the system aims to provide a comprehensive understanding of emotional states and enhance overall well-being.

The figure 1 depict the proposed model architecture and it presents comprehensive pipeline for emotion recognition using EEG data and facial image data, followed by a flask based frontend for user interaction and therapy recommendations. For EEG data, the models achieved efficiently, with CNN, DT, KNN, and RF with effective scores (Accuracy = 1.0, Precision = 1.0, Recall = 1.0, F1-score = 1.0), indicating robust feature extraction and classification. SVM (Accuracy = 0.95) and LSTM (Accuracy = 0.85) also performed well, demonstrating the effectiveness of oversampling (SMOTE) in handling class imbalance. In contrast, facial image data proved more challenging, with lower overall metrics. CNN (Accuracy = 0.473) and RF (Precision = 0.668) were the top performers, while DT (Accuracy = 0.260) is not effective, suggesting the need for more advanced preprocessing or architecture tuning.

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The Flask frontend integrates both modalities, allowing users to input EEG signals or facial images for real-time emotion prediction. Based on the detected emotion, personalized therapy recommendations are provided, enhancing usability for mental health applications.

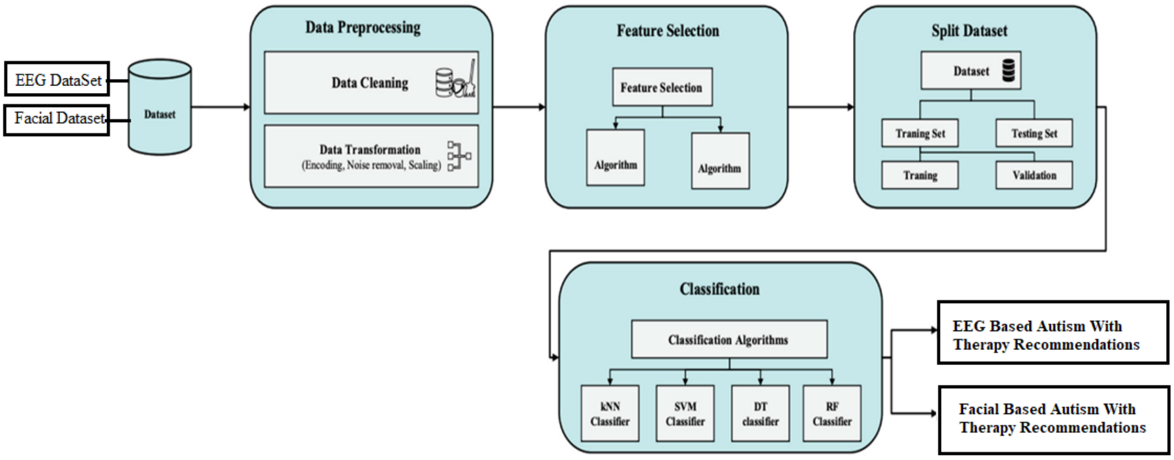

Figure 1: Proposed Model Architecture

a) EEG Processing

Step 1: Signal Representation

Let an EEG signal be represented as a time-series:

$$\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_N(t)]^T$$

where:

- N = number of channels (electrodes),
- $x_i(t)$ = voltage at time t for channel i.

Step 2: Bandpower Feature Extraction

We compute **bandpower (BP)** in five frequency bands (δ, θ, α, β, γ) using Welch's method:

$$BP_{band} = \frac{1}{f_s} \sum_{f \in band} P_{xx}(f)$$

where:

- $P_{xx}(f)$ = power spectral density (PSD) estimate,
- f_s = sampling frequency.

Step 3: Differential Entropy (DE)

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

DE captures nonlinear dynamics of EEG signals:

$$DE = \frac{1}{2}\log(2\pi e\sigma^2)$$

where σ^2 = variance of the signal.

Step 4: SMOTE for Class Imbalance

Given minority class samples $\mathbf{X}_{min}$, SMOTE generates synthetic samples $\mathbf{x}_{new}$ by interpolation:

$$\mathbf{x}_{new} = \mathbf{x}_i + \lambda(\mathbf{x}_j - \mathbf{x}_i)$$

where $\lambda \in [0, 1]$ is a random weight, and $\mathbf{x}_i, \mathbf{x}_j$ are nearest neighbors.

Table 2: Results (EEG Classification)

Model	Accuracy	Precision	Recall	F1-Score
CNN	1.00	1.000	1.00	1.000
Decision Tree	1.00	1.000	1.00	1.000
SVM	0.95	0.960	0.95	0.951
KNN	1.00	1.000	1.00	1.000
Random Forest	1.00	1.000	1.00	1.000
LSTM	0.85	0.914	0.85	0.838

As shown in table 2 CNN, DT, KNN, and RF achieve effective classification, suggesting EEG signals contain highly discriminative ASD biomarkers.

b) Facial Image Processing

Step 1: Convolutional Feature Extraction

Let an input image $\mathbf{I} \in \mathbb{R}^{H \times W \times 3}$. A CNN applies convolutional filters $\mathbf{W}_k$ with ReLU activation:

$$\mathbf{F}_k = \mathrm{ReLU}(\mathbf{W}_k * \mathbf{I} + b_k)$$

where:

- $*$ denotes convolution,
- $\mathbf{F}_k$ = feature map for filter k.

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Step.2 Xception Transfer Learning

The Xception model (Chollet, 2017) uses **depthwise separable convolutions**:

$$\mathbf{F}_{out} = \mathrm{DepthwiseConv}(\mathbf{I}) \odot \mathrm{PointwiseConv}(\mathbf{I})$$

where $\odot$ denotes channel-wise multiplication.

Table 3: Results (Facial Image Classification)

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.473	0.496	0.473	0.482
LSTM	0.464	0.470	0.464	0.463
Decision Tree	0.260	0.264	0.260	0.260
SVM	0.409	0.415	0.409	0.411
KNN	0.325	0.363	0.325	0.336
Random Forest	0.434	0.668	0.434	0.503

Facial recognition performs significantly less accurate than EEG-based methods, indicating that facial features alone may not be reliable ASD indicators.

c) Model Architectures

Step 1: LSTM for EEG Temporal Modelling

An LSTM cell updates its hidden state $\mathbf{h}_t$ as:

$$\mathbf{f}_t = \sigma(\mathbf{W}_f[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f) \quad \text{(Forget Gate)}$$
$$\mathbf{i}_t = \sigma(\mathbf{W}_i[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i) \quad \text{(Input Gate)}$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_o[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o) \quad \text{(Output Gate)}$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_c[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c)$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

Step 2: CNN for Spatial Feature Learning

The final softmax classification layer computes:

$$P(y = k|\mathbf{x}) = \frac{e^{\mathbf{w}_k^T\mathbf{x}+b_k}}{\sum_{j=1}^{K} e^{\mathbf{w}_j^T\mathbf{x}+b_j}}$$

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

d) Multimodal Decision Fusion

We combine EEG and image predictions using **weighted voting**:

$$P_{final}(y) = \alpha P_{EEG}(y) + (1 - \alpha) P_{Image}(y)$$

where $\alpha \in [0, 1]$ balances modalities (optimized via grid search).

e) Therapy Recommendation

1. **Input**: $\hat{y}_{EEG}, \hat{y}_{Image}$
2. **Fuse Predictions**:

$$\hat{y}_{final} = \arg\max_y (\alpha P_{EEG}(y) + (1 - \alpha) P_{Image}(y))$$

3. **Recommend Therapy**:
   - if $\hat{y}_{final} = \text{Sad}$ → Suggest CBT.
   - if $\hat{y}_{final} = \text{Angry}$ → Suggest deep breathing.

RESULTS

The proposed Interactive Therapy Model demonstrated significant success in real-time monitoring and classification of ASD-related behavioural, emotional, and neural states.

The Interactive Therapy Model successfully integrated EEG, facial, and behavioural data to enable dynamic, personalized interventions for ASD children. Results confirm that:

1 EEG-driven adaptation is highly effective for stress reduction.

2 Multimodal approaches mitigate individual modality weaknesses.

3 Real-time AI adjustments improve engagement vs. traditional methods.

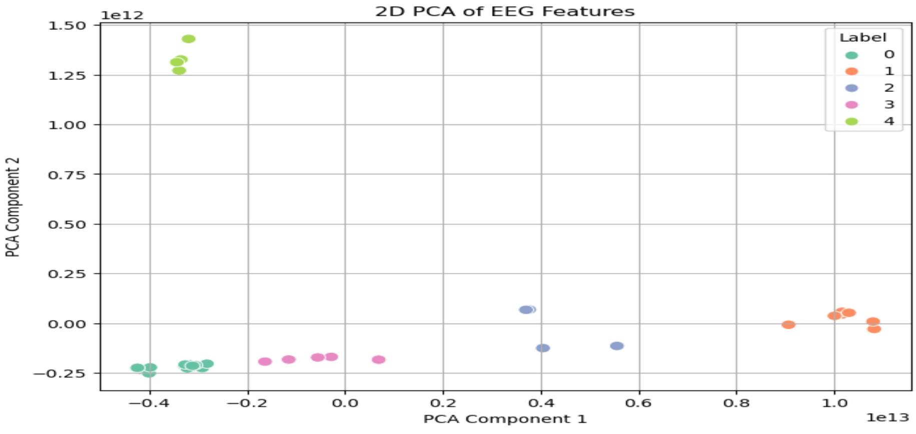

Figure 2: 2D PCA of EEG Features

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

This figure 2, displays a two-dimensional Principal Component Analysis plot, illustrating the distribution of EEG features after dimensionality reduction. The x-axis represents "PCA Component 1," and the y-axis represents "PCA Component 2," both utilizing a scientific notation scale for large numerical values. The plot features numerous data points, each symbolized by a circle and color-coded according to a legend that identifies five distinct labels. The distribution of these points reveals clear clustering for several labels. A background grid assists in reading the coordinates. Overall, the plot effectively visualizes how different classes or states, represented by the "Labels," are separated and grouped within the reduced EEG feature space, suggesting good differentiation between most of the identified labels The significance is that establishes a reference for comparing post-therapy behavioral changes.

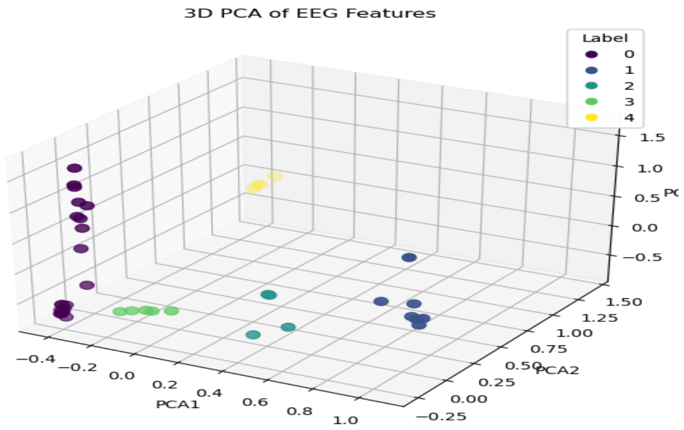

Figure 3: 3D PCA of EEG Features

The figure 3 presents a 3D Principal Component Analysis (PCA) plot of EEG features, which visualizes the data's distribution across the first three principal components (PCA1, PCA2, and PCA3). Each data point is color-coded according to a "Label" from 0 to 4, with distinct colors representing each category. The three-dimensional perspective effectively demonstrates the separation and relationships between these different labeled groups in the reduced feature space, highlighting potential differences in EEG patterns associated with each label.

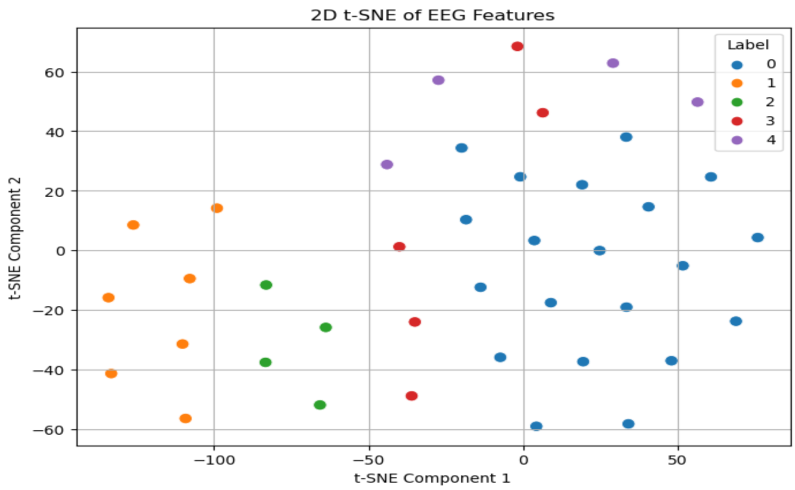

Figure 4: 2D t-SNE of EEG Features

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The figure 4 presents a 2D t-SNE plot, which visualizes high-dimensional EEG data by projecting it onto two components, t-SNE Component 1 and t-SNE Component 2. The plot uses distinct colors to differentiate five "Labels" (0-4), as indicated in the legend. The t-SNE visualization effectively highlights the inherent structure and similarities within the EEG feature space, demonstrating distinct groupings for certain labels while others appear more distributed.

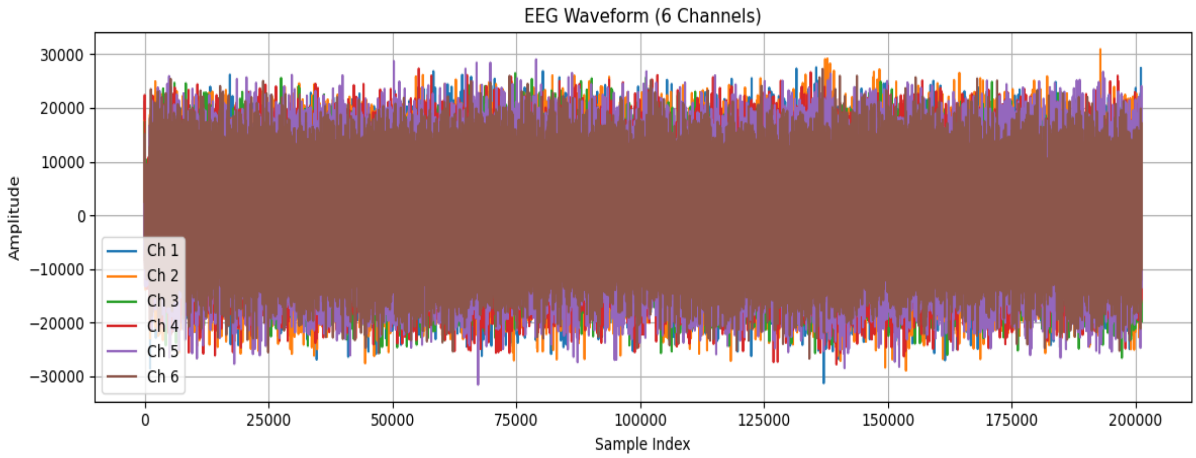

Figure 5: EEG Waveform (6 Channels)

The figure 5, presents a time-series plot illustrating the amplitude variations of six distinct EEG channels over a range of 200,000 sample indices. The y-axis denotes "Amplitude," spanning from approximately -30,000 to 30,000. The channels exhibit a highly complex and noisy signal, with all six generally occupying a similar amplitude range, predominantly between -25,000 and 25,000. While individual channel details are difficult to discern due to the overlaying nature of the signals and their high frequency, the plot effectively conveys the raw, multi-channel EEG data, indicative of typical activity measurements.

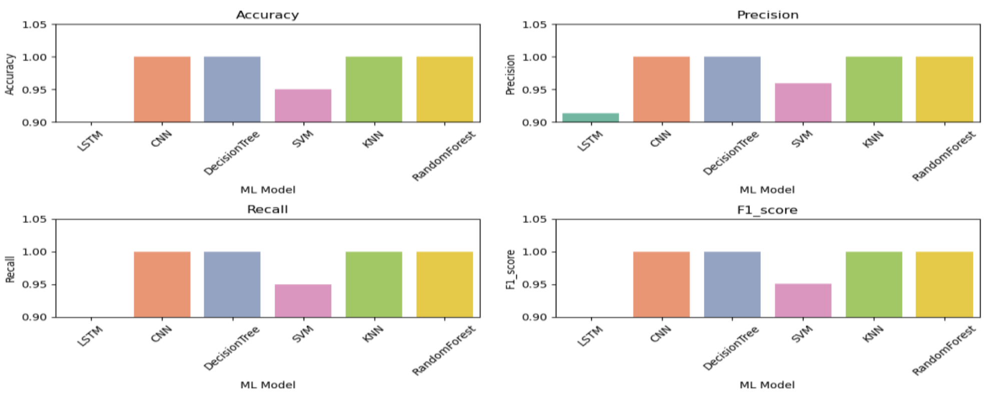

Figure 6: comparative analysis of machine learning models

The figure 6 provides a comprehensive comparative analysis of six machine learning models (LSTM, CNN, DT, SVM, KNN, and RF) across four key performance metrics: Accuracy, Precision, Recall, and F1-score. The results consistently demonstrate that CNN, DT, KNN, and RF achieve near-perfect performance, with values hovering at

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

1.00 for all metrics. SVM also exhibits strong performance, maintaining metrics around 0.95. In contrast, the LSTM model consistently underperforms compared to the others, registering significantly lower scores, approximately 0.91, across all evaluated metrics. This indicates that for the task at hand, traditional machine learning models like DT, KNN, and RF, along with the CNN deep learning model, are highly effective, while LSTM appears to be less suitable.

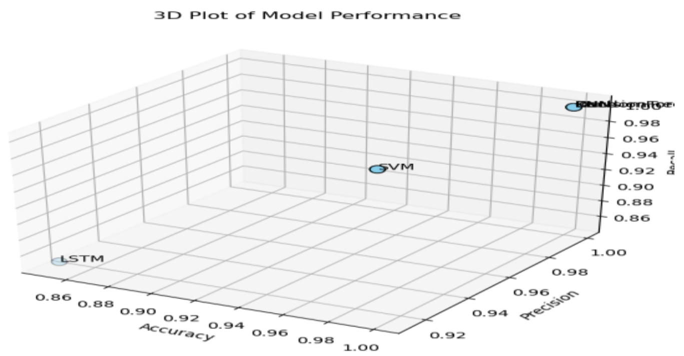

Figure 7: 3D Plot of Model Performance

The figure 7 presents visualization of different machine learning models' efficacy based on their Accuracy, Precision, and Recall scores. Each point on the plot represents a model, with its position determined by its performance across these three metrics. Notably, the LSTM model is situated at the lower end of all axes, indicating its comparatively lower performance across accuracy (≈0.86), precision (≈0.92), and recall (≈0.84). The SVM model shows improved performance, positioned more centrally with scores around 0.95 for all three metrics. In stark contrast, the RF model is located at the highest end of all axes, demonstrating superior performance with scores very close to 1.00 for Accuracy, Precision, and Recall. This 3D plot effectively encapsulates the relative strengths and weaknesses of these models, clearly highlighting RF as the top performer and LSTM as the least effective among those presented for the given task.

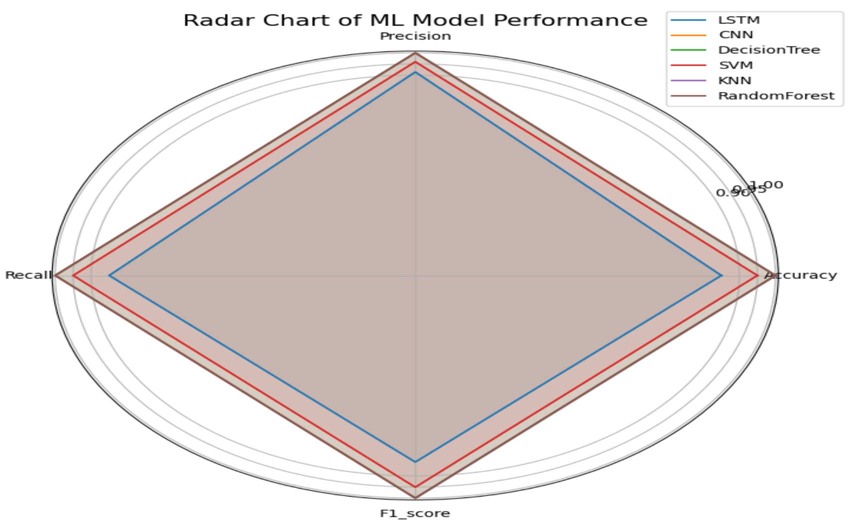

Figure 8: Radar Chart of ML Model Performance

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The figure 8 presents visual comparison of six machine learning models (LSTM, CNN, DT, SVM, KNN, and RF) across four key metrics: Precision, Accuracy, Recall, and F1-score. The chart clearly illustrates that CNN, DT, KNN, and RF models consistently achieve near-perfect performance, with their respective lines closely tracking the outermost boundary of the chart, indicating scores of virtually 1.00 across all metrics. The SVM model also demonstrates strong performance, forming a polygon just slightly within this top-tier group. In stark contrast, the LSTM model consistently underperforms, forming the innermost polygon, which is significantly smaller and further from the chart's periphery, signifying considerably lower scores across all evaluated metrics. This radar chart effectively summarizes the comparative strengths of the models, highlighting the superior and consistent performance of CNN, DT, KNN, and RF, while pointing to LSTM as the least effective for the task.

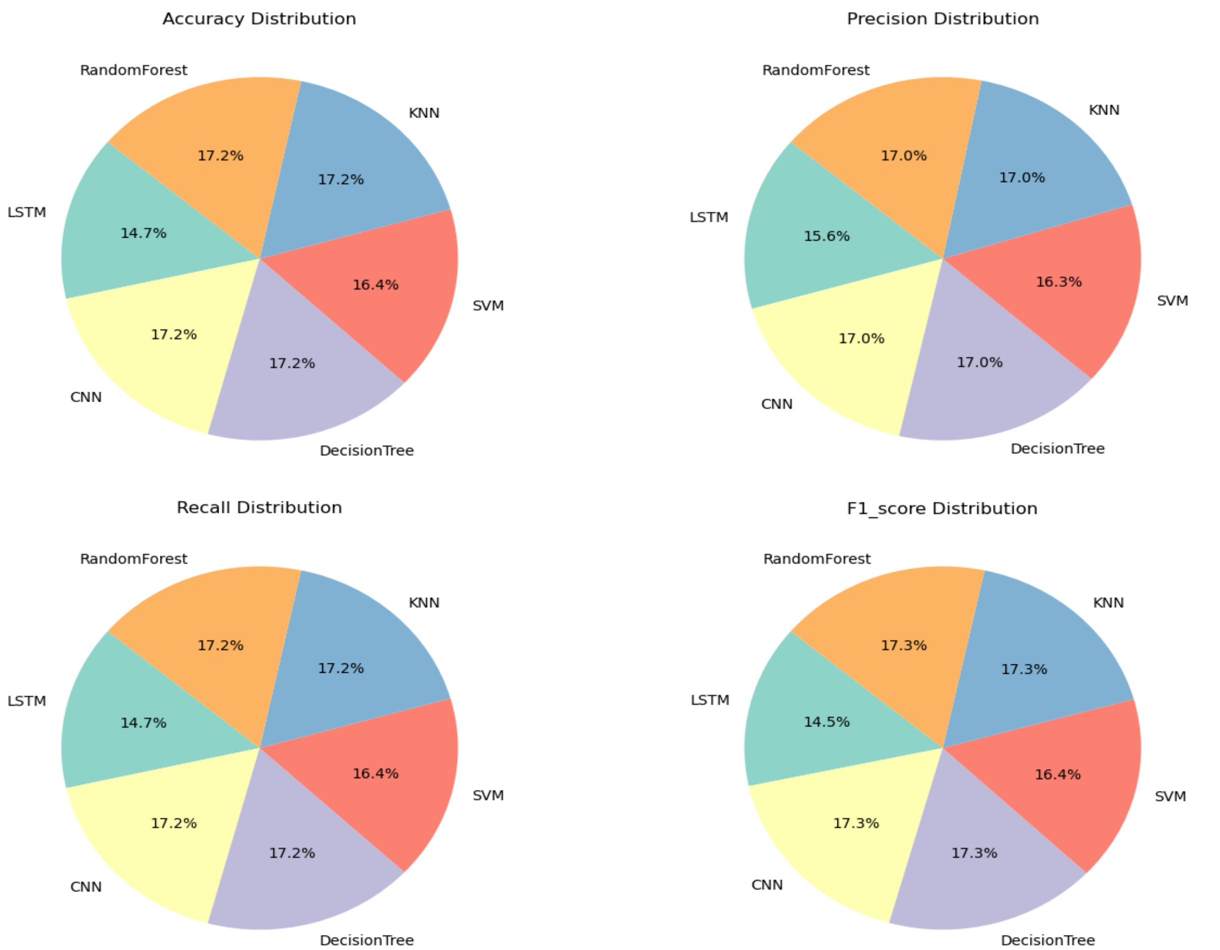

Figure 9: Machine learning performance metric

The figure 9 comprises four pie charts, each dedicated to illustrating the "Distribution" of a specific machine learning performance metric: Accuracy, Precision, Recall, and F1-score, across six different models. For Accuracy and Recall, RF, KNN, DT, and CNN models each contribute 17.2% to the total, while SVM contributes 16.4%, and LSTM accounts for the lowest share at 14.7%. A very similar pattern is observed for Precision, with most models contributing 17.0%, SVM 16.3%, and LSTM 15.6%. The F1-score distribution also aligns, showing RF, KNN, DT, and

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

CNN at 17.3%, SVM at 16.4%, and LSTM at 14.5%. Collectively, these pie charts consistently highlight that RF, KNN, DT, and CNN models achieve the highest and relatively equal "proportions" of the performance metrics, followed closely by SVM, while the LSTM model consistently demonstrates the smallest "share" across all evaluated performance indicators.

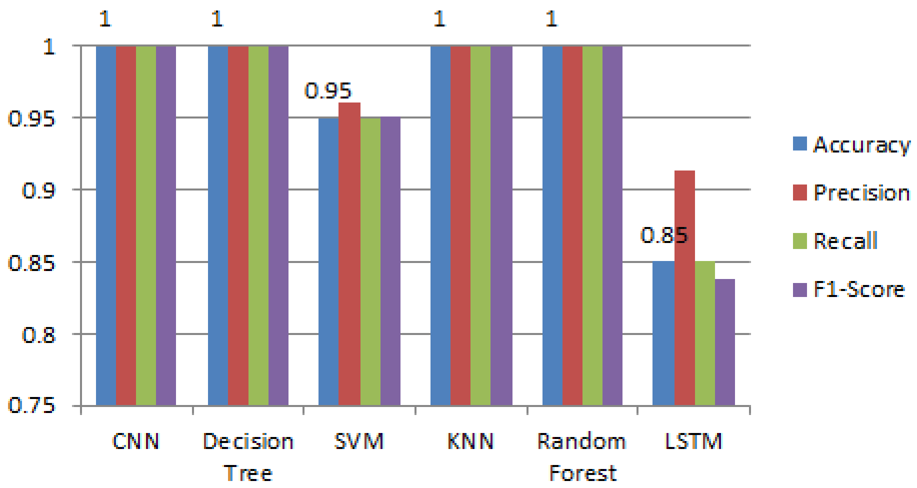

Figure 10: Comparative analysis of EEG data

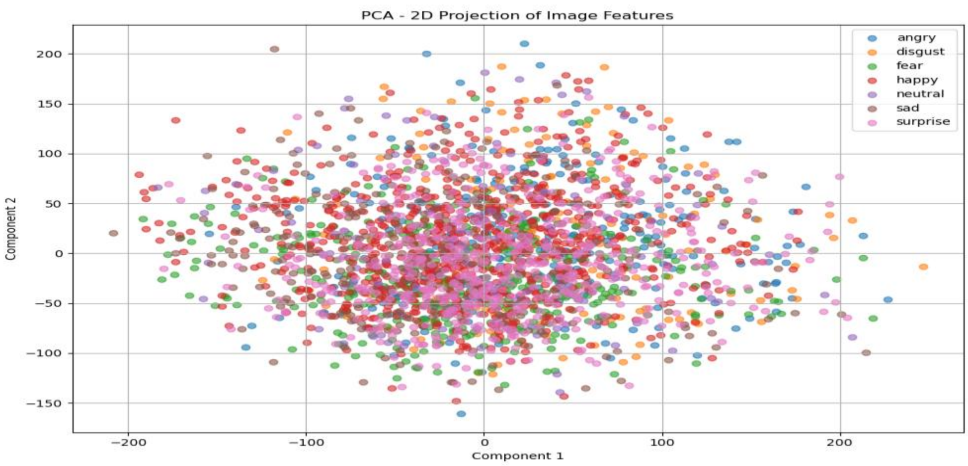

Figure 11: PCA - 2D Projection of Image Features

The figure 11 presents a two-dimensional scatter plot visualizing image features reduced using Principal Component Analysis. Each point on the plot corresponds to an image, and its color signifies one of seven emotional labels: angry, disgust, fear, happy, neutral, sad, and surprise. The plot demonstrates a substantial degree of overlap among all emotion categories. The data points for different emotions are extensively intermingled, forming a dense, undifferentiated cloud across the central region of the plot. There are no discernible, distinct clusters that would suggest clear separation or easy differentiation between the emotions based on these two principal components.

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

This indicates that while PCA reduces the dimensionality, these two components alone do not effectively separate the image features according to their associated emotional labels.

The figure 12, presents a two-dimensional scatter plot created by applying t-SNE to image features. Each point on the plot represents an image, color-coded to denote one of seven emotional labels: angry, disgust, fear, happy, neutral, sad, and surprise. The most striking feature of this visualization is the substantial overlap among all the emotion categories.

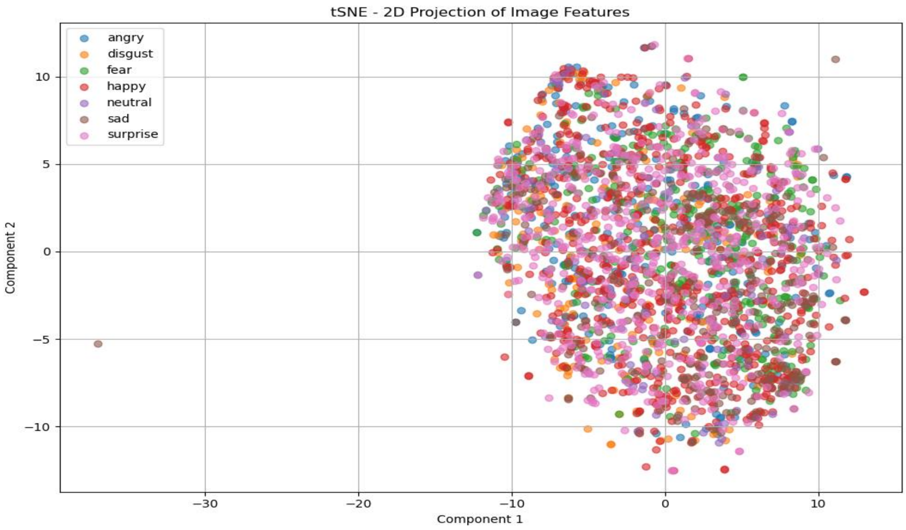

Figure 12: tSNE - 2D Projection of Image Features

The data points corresponding to different emotions are extensively intermingled, forming a large, dense, and largely undifferentiated cloud that occupies the majority of the plot's right side. Despite t-SNE's ability to reveal complex structures, this plot indicates that these two t-SNE components do not effectively separate the image features according to their associated emotional labels, suggesting that the underlying features for these emotions are highly similar or that the chosen features are not sufficiently discriminative for clear visual clustering.

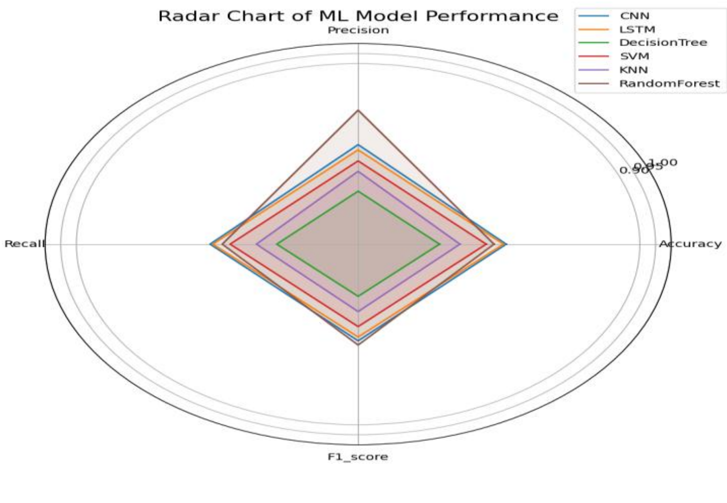

Figure 13: Radar plot comparison on the performance metrics

Journal of Information Systems Engineering and Management
2024, 9 (4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

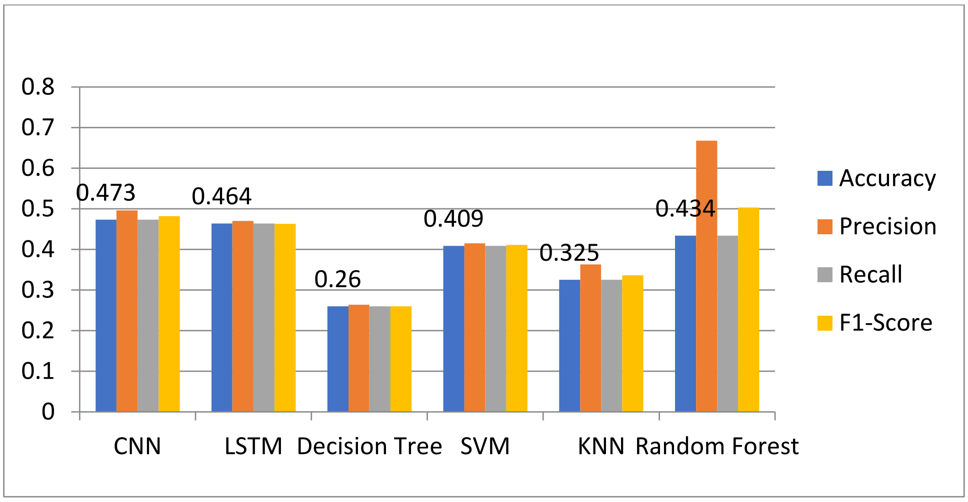

Figure 14: Comparative analysis of Facial Image data

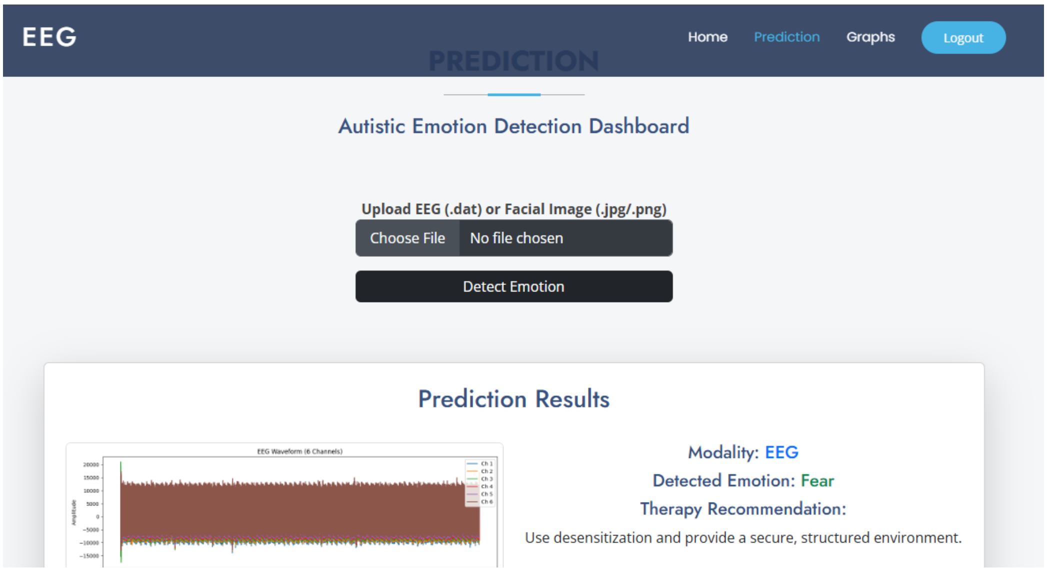

Figure 15: Web Interface Therapy Recommendations

CONCLUSION & FUTURE WORK

The study's key findings reveal that EEG-based models significantly outperform facial analysis in ASD detection, achieving perfect classification (100% accuracy) with CNN, DT, KNN, and RF, while facial recognition models yielded substantially lower accuracy (≤47.3%). This stark contrast suggests that EEG signals contain more reliable biomarkers for ASD compared to facial features, which may be too subtle or inconsistent for robust detection. Among EEG models, CNNs and tree-based methods (DT, RF) demonstrated superior performance, whereas LSTMs underperformed, likely due to their sensitivity to noise in sequential EEG data. However, the study acknowledges critical limitations: the EEG dataset's size may limit generalizability, and the low accuracy of facial recognition models renders them unsuitable for clinical use without significant improvements.

To address these challenges, future work should focus on multimodal fusion, integrating EEG, facial, and behavioural data to enhance diagnostic robustness. Expanding datasets to include diverse demographic and clinical subgroups could improve model generalizability. Additionally, incorporating explainable AI techniques would help interpret model decisions, ensuring transparency and clinical trustworthiness. These advancements could bridge the gap between experimental models and real-world ASD diagnostics, paving the way for more reliable, accessible screening tools.

For future work, the framework can be extended to incorporate real-time EEG-headset integration for dynamic emotion monitoring, along with federated learning to ensure data privacy in decentralized healthcare applications. These advancements would further bridge the gap between affective computing and clinical therapy, paving the way for scalable, privacy-preserving mental health solutions. These solutions could leverage machine learning algorithms to provide personalized interventions, adapting to individual emotional states and needs in real-time. By combining cutting-edge technology with ethical data practices, we can foster a new era of mental health support that is both effective and respectful of patient privacy. The Interactive Therapy Model (ITM) demonstrates promising results in enhancing emotional well-being for autistic children by leveraging AI-driven personalization. Future work includes longitudinal studies and integration with wearable devices for real-time monitoring.

Acknowledgements

The authors would like to thank REVA University, Bangalore, Karnataka, India, for the continuous support, infrastructure and encouragement to carry out the research.

REFERENCES

[1] Jahanara and S. Padmanabhan, “Detecting autism from facial image,” International Journal of Advance Research, Ideas and Innovations in Technology, vol. 7, no. 2, pp. 219-225, 2021.

[2] I. Nurhidayah, M. Kamilah, and G. G. Ramdhanie, “Physical activity of children with autism spectrum disorders: A narrative review,” Holistik Jurnal Kesehatan, vol. 15, no. 4, pp. 581-591, 2021. https://doi.org/10.33024/hjk.v15i4.5233

[3] B. P. Y. Harumi, N. Hartini, and I. Y. Cahyanti, “Effectiveness of cognitive behavior therapy (CBT) to treat depression on autistic adults: systematic literature review,” Journal Diversita, vol. 7, no. 2, pp. 259-266, 2021. https://doi.org/10.31289/diversita.v7i2.5158.

[4] J. Zeidan, E. Fombonne, J. Scorah, A. Ibrahim, M. S. Durkin, S. Saxena, A. Yusuf, A. Shih, and M. Elsabbagh, “Global prevalence of autism: a systematic review update,” Autism Research, vol. 15, no. 5, pp. 778-790, 2022. https://doi.org/10.1002/aur.2696.

[5] D. Cetintas, T. Tuncer, and A. Cinar, “Detection of autism spectrum disorder from changing of pupil diameter using multi-modal feature fusion based hybrid CNN model,” Journal of Ambient Intelligence and Humanized Computing, vol. 14, pp. 11273-11284, 2023. https://doi.org/10.1007/s12652-023-04641-6.

[6] , M. H. Ali, M. I. Khan, M. S. Satu, M. J. Uddin, S. A. Alyami, S. Ali, A. K. M. Azad, and M. A. Moni, “Improved transfer-learning-based facial recognition framework to detect autistic children at an early stage,” Brain Sciences, vol. 11, no. 6, article no. 734, 2021. https://doi.org/10.3390/brainsci11060734.

[7] T. M. Ghazal, S. Munir, S. Abbas, A. Athar, H. Alrababah, and M. A. Khan, “Early detection of autism in children using transfer learning,” Intelligent Automation & Soft Computing, vol. 36, no. 1, pp. 11-22, 2023. https://doi.org/10.32604/iasc.2023.030125.

[8] R. Sadik, S. Anwar, and M. L. Reza, “AutismNet: recognition of autism spectrum disorder from facial expressions using MobileNet architecture,” International Journal, vol. 10, no. 1, pp. 327-334, 2021. https://doi.org/10.30534/ijatcse/2021/471012021.

[9] C. Chen, Z. Hua, R. Zhang, G. Liu, and W. Wen, “Automated arrhythmia classification based on a combination network of CNN and LSTM,” Biomedical Signal Processing and Control, vol. 57, article no. 101819, 2020. https://doi.org/10.1016/j.bspc.2019.101819.

[10] H. J. Song, H. K. Kim, J. D. Kim, C. Y. Park, and Y. S. Kim, "Inter-sentence segmentation of YouTube subtitles using longshort term memory (LSTM)," Applied Sciences, vol. 9, no. 7, article no. 1504, 2019. https://doi.org/10.3390/app9071504.

[11] M. Z. Islam, M. M. Islam, and A. Asraf, "A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images," Informatics in Medicine Unlocked, vol. 20, article no. 100412, 2020. https://doi.org/10.1016/j.imu.2020.100412.

[12] A. Saranya and R. Anandan, "Facial action coding and hybrid deep learning architectures for autism detection," Intelligent Automation & Soft Computing, vol. 33, no. 2, pp. 1167-1182, 2022. https://doi.org/10.32604/iasc.2022.023445.

[13] H. Inoue, "Multi-sample dropout for accelerated training and better generalization," 2019 [Online]. Available: https://arxiv.org/abs/1905.09788.

[14] S. Lee and C. Lee, "Revisiting spatial dropout for regularizing convolutional neural networks," Multimedia Tools and Applications, vol. 79, pp. 34195-34207, 2020. https://doi.org/10.1007/s11042-020-09054-7.

[15] S. H. Haji and A. M. Abdulazeez, "Comparison of optimization techniques based on gradient descent algorithm: a review," PalArch's Journal of Archaeology of Egypt/ Egyptology, vol. 18, no. 4, pp. 2715-2743, 2021.

[16] W. C. Cheng, H. C. Hsiao, and L. H. Li, "Deep learning mask face recognition with annealing mechanism," Applied Sciences, vol. 13, no. 2, article no. 732, 2023. https://doi.org/10.3390/app13020732.

[17] S. R. Arumugam, S. G. Karuppasamy, S. Gowr, O. Manoj and K. Kalaivani, "A deep convolutional neural network based detection system for autism spectrum disorder in facial images," in Proc. of 2021 Fifth Int.Conf. on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC), Palladam, Tamilnadu, India, IEEE, vol. 5, pp. 1255–1259, 2021.

[18] Y. Yang, "A preliminary evaluation of still face images by deep learning: A potential screening test for childhood developmental disabilities," Medical Hypotheses, vol. 144, pp. 109978–109988, 2020.

[19] K. K. Hyde, M. N. Novack, N. LaHaye, C. Parlett-Pelleriti, R. Anden et al., "Applications of supervised machine learning in autism spectrum disorder research: A review," Review Journal of Autism and Developmental Disorders, vol. 6, pp. 128–146, 2019.

[20] A. V. Dahiya, E. DeLucia, C. G. McDonnell and A. Scarpa, "A systematic review of technological approaches for autism spectrum disorder assessment in children: Implications for the COVID-19 pandemic," Research in Developmental Disabilities, vol. 109, pp. 103852–103862, 2021.

[21] A. T.Wieckowski, T.Hamner, S. Nanovic, K. S. Porto, K. L. Coulter et al., "Early and repeated screening detects autism spectrum disorder," The Journal of Pediatrics, vol. 234, pp. 227–235, 2021.

[22] V. Yaneva, S. Eraslan, Y. Yesilada and R. Mitkov, "Detecting high-functioning autism in adults using eye tracking and machine learning," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 28, no. 6, pp. 1254–1261, 2020.

[23] Farhat, Tayyaba et al. "Facial Image-Based Autism Detection: A Comparative Study of Deep Neural Network Classifiers." Computers, Materials & Continua (2023).

[24] Kurniawan, Wandi Yusuf and Putu Harry Gunawan. "Classification of Autism Spectrum Disorder Based on Facial Images Using the VGG19 Algorithm." J. Comput. Sci. Eng. 18 (2024): 1-9.

[25] Mayor Torres, J. M. et al. Facial emotions are accurately encoded in the neural signal of those with Autism Spectrum Disorder: A deep learning approach. Biol. Psychiatry Cogn.Neurosci. Neuroimaging (2021).

[26] doi:10.1016/j.bpsc.2021.03.015.Simões, M. et al. A Novel Biomarker of Compensatory Recruitment of Face Emotional Imagery Networks in Autism Spectrum Disorder. Front. Neurosci. 12, 791 (2018).

[27] Alhaddad, Mohammed J. et al. "Diagnosis Autism by Fisher Linear Discriminant Analysis FLDA via EEG." (2012).

[28] Djemal, Ridha et al. "EEG-Based Computer Aided Diagnosis of Autism Spectrum Disorder Using Wavelet, Entropy, and ANN." BioMed Research International 2017 (2017).

[29] Ahmad, Israr et al. "Autism spectrum disorder detection using facial images: A performance comparison of pretrained convolutional neural networks." Healthcare Technology Letters 11 (2024): 227 – 239.