Deep Learning-Based Methodology for Early Detection of Autism Spectrum Disorder

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***Abstract* —** Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disease characterised by difficulties in social interaction, communication, behaviour, and sensory processing. Early identification is important because it allowsfor prompt treatments, which can alter an individual's lifelong trajectory and general well-being. However, the complications in detecting ASD in its early stages persist dueto the dependence on subjective judgements and clinical observations. These old techniques may miss tiny indications throughout important developmental phases, perhaps resulting in delayed intervention. As a result, there is a vital need to research creative approaches to improve the accuracy and capability of early ASD identification, for example, deep machine learning. By leveraging the power of data-driven analysis, such as behavioural patterns, neuroimaging findings, and genetic insights, deep learning could provide a revolutionary avenue for more precise and timely interventions, ultimately improving the outcomes and quality of life for individuals with ASD. This chapter will propose a deep learning-based approach for the early diagnosis of Autism, with the potential to automate and enhance the disorder's early diagnosis while also allowing for faster therapy, resulting in better outcomes for persons with ASD. The combination of deep learning technology with the challenges of early ASD identification provides a promising approach to improving the lives of people on the autistic spectrum. By exploiting the power of deep learning, we are on the verge of revolutionising the identification, diagnosis, and support of persons with ASD, which will eventually lead to better results and a more inclusive society.

***Index Terms*—** Autism Spectrum Disorder (ASD), Deep Learning (DL), Neural Networks, neurodevelopmental disorders, Behavioural analysis, Neuroimaging, Genetic data, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVMs), Random Forests.

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder marked by difficulties with communication and behavioural feedback. Early detection and intervention are critical for enhancing long-term impact for people with ASD [1]. Deep learning-based approaches have emerged as significant tools in a variety of disciplines, including healthcare, in recent years. These new computational approaches have shown enormous potential in revolutionising ASD early diagnosis, resulting in more timely treatments and enhanced quality of life for afflicted persons [2].

Traditional ASD diagnosis procedures frequently rely on behavioural observations and lengthy clinical exams, which can be time-consuming and prone to human mistakes. Deep learning, a type of artificial intelligence (AI), has the potential to alter this process by automatically analysing massive volumes of data to uncover tiny patterns and correlations that the human eye may miss. This capacity to identify complex information from disparate data sources has opened up new paths for ASD identification in the early stages [3].

Deep learning approaches have the capacity to analyse a wide range of data sources, including medical pictures, audio recordings, and behavioural data. Convolutional neural networks (CNNs), for example, excel in analysing medical imagery such as brain scans, enabling the diagnosis of structural abnormalities or changes in brain areas associated with ASD. Recurrent neural networks (RNNs) are similarly good at processing sequential input, making them suited for analysing speech patterns and social interactions [4].

Deep learning models can also combine numerous sources of information, allowing for a more thorough examination of ASD-related issues. These tools can reveal complicated links that help our knowledge of the condition by integrating data from genetic investigations, brain imaging, and behavioural evaluations. This comprehensive strategy improves the accuracy and dependability of early ASD detection approaches [5].Furthermore, advances in deep learning algorithms, as well as the availability of massive datasets, have substantially increased the precision and efficiency of ASD diagnosis. Researchers and physicians may now use these tools to detect subtle signals of ASD at a younger age, often even before overt symptoms appear. This early detection is crucial for launching therapies during the key developmental period when the brain is more flexible [6]. Figure 1.1 displays the different symptoms of Autism Spectrum Disorder.

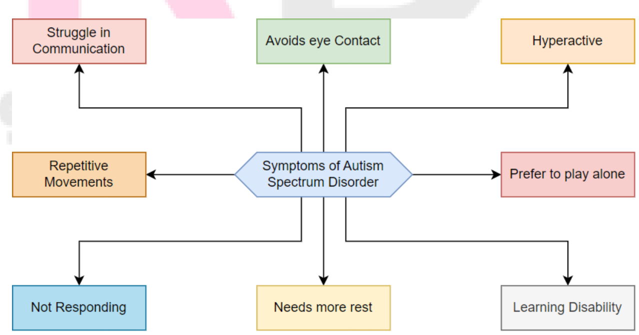

Figure 1.1: Symptoms of Autism Spectrum Disorder

Despite significant advances, obstacles remain in the use of deep learning algorithms for ASD identification. The importance of ethical issues, data protection, and interpretability in assuring the appropriate deployment of these technologies cannot be overstated. Researchers are working hard to solve these problems, with the goal of developing transparent and ethical AI systems that can be smoothly integrated into clinical practice [7].

Collaboration amongst interdisciplinary teams of computer scientists, neuroscientists, clinicians, and psychologists is critical in developing and validating deep learning-based ASD detection approaches. Such collaborations promote information sharing, ensuring that these treatments are not only technologically advanced but also therapeutically relevant and culturally appropriate [8].

Deep learning-based strategies for early ASD identification are evolving and have the potential to revolutionise the landscape of autism diagnosis and treatments. Early detection of ASD allows for timely access to appropriate therapies and support services, improving the overall quality of life for people on the autistic spectrum and their families. Furthermore, early discovery provides essential data to current research initiatives, enhancing our grasp of ASD's complicated aetiology [9].

Staying up to date on the newest advancements in this fast-expanding profession is critical for physicians, researchers, and policymakers. As deep learning algorithms grow more complex and widely available, it is critical to develop a collaborative atmosphere that promotes the appropriate use of these technologies. We may realise the full promise of deep learning-based approaches in the early identification of Autism Spectrum Disorder by combining scientific rigour, ethical concerns, and compassionate care [10].

This work seeks to give a nuanced perspective of the present state of research, problems faced, and future possibilities through a comprehensive analysis of deep learning-based strategies for early ASD identification. We may set the path for a future in which persons with ASD get timely and personalised treatments that promote their development, well-being, and integration into society by diving into the complexities of these novel techniques [11].

The use of deep learning-based approaches in ASD diagnosis not only improves identification accuracy but also allows for more personalised treatment options. These approaches can detect small differences in symptoms and responsiveness to therapies among people with ASD by analysing large datasets from varied populations. This granularity allows doctors to customise therapy to particular requirements, maximising efficacy and, ultimately, improving outcomes for patients diagnosed with the illness [12].

Furthermore, the use of deep learning in the early diagnosis of ASD overcomes geographical boundaries and socioeconomic differences. Individuals living in rural places or underprivileged communities can now benefit from enhanced diagnostic tools thanks to the introduction of telehealth services and digital health platforms. This healthcare democratisation empowers families and communities, ensuring that even individuals with limited access to specialised medical facilities obtain early and accurate ASD

diagnoses for their loved ones [13].

Deep learning has the ability to provide information on the underlying molecular and genetic causes of ASD, in addition to its diagnostic applications. Researchers can discover novel avenues for targeted therapies and therapeutic improvements by analysing genetic data and discovering unique biomarkers related with ASD risk. This multimodal approach not only assists in early identification but also increases our understanding of the underlying elements of ASD, opening the path for future more effective therapies and interventions [14].

Furthermore, current deep learning research involves refining existing algorithms and developing novel techniques. As these approaches advance, they have the potential to not only identify ASD but also forecast its progression. Early diagnosis of high-risk people, as well as analysing the disorder's course through time, can have a substantial influence on therapeutic options. Anticipating the particular problems that persons with ASD may confront at various developmental stages allows for the establishment of specialised support systems that enhance their social, intellectual, and occupational successes [15].

The use of deep learning-based approaches to the early identification of Autism Spectrum Disorder marks a watershed point in the study of neurodevelopmental diseases. We are not only enhancing the accuracy and efficiency of diagnoses, but we are also extending our grasp of the complexity of ASD by utilising the computational power of artificial intelligence. As these technologies progress, they provide hope to countless families and individuals afflicted by ASD, offering a future in which early intervention is not only a possibility but a common reality, altering lives and creating a more inclusive society for all [16].

2. WHY IS THERE A NEED OF EARLY DETECTION OF AUTISM

Early identification of Autism Spectrum Disorder (ASD) is critical for a variety of reasons, each emphasising the necessity of immediate intervention and support for individuals and their families. Here are a few main reasons why early autism identification is critical:

- Early Intervention Improves Outcomes: Early intervention therapies, like as behavioural therapy and speech therapy, have repeatedly been proven in studies to improve the outcomes of people with ASD. Intervening during a vital developmental stage can assist youngsters in acquiring necessary skills, improving communication ability, and improving social connections. The sooner these treatments are implemented, the greater the favourable influence on a child's overall development [17]
- Facilitates Access to Support Services: Early identification enables families to have access to necessary support services and resources. Parents may learn about ASD and techniques to assist their child's

special needs. Access to specialised therapies, educational programmes, and community support services can improve a child's quality of life and future prospects dramatically.

- Reduces Parental Stress: Knowing about a child's autism spectrum disorder diagnosis early on might help parents better comprehend their child's behaviour and issues. It helps minimise parental anxiety and ambiguity by offering a clear explanation for the child's challenges. When parents are well-informed and have adequate coping mechanisms, they may better assist their kid and build a more pleasant home atmosphere [18].
- Enables Tailored Education and Support: Early detection enables educators to develop individualised education plans (IEPs) that are customised to the unique requirements of the child. Teachers and support personnel may promote a more inclusive learning environment by implementing evidence-based techniques and modifications. Tailored support ensures that the kid receives the right amount of help and encouragement, maximising their educational experience [19].
- Enhances Social and Communication Skills: Early therapies frequently concentrate on developing social and communication skills, which are major obstacles for people with ASD. Targeted therapy and interventions can help youngsters develop language and communication skills, as well as increase their capacity to engage with classmates and family members. These abilities are necessary for forming connections and handling social situations throughout one's life [20].
- Supports Family Dynamics: Early identification allows families to prepare for the particular challenges of raising an autistic kid. Counselling and support services are available to assist parents and siblings cope with the emotional and practical elements of having a special needs family member. Understanding the diagnosis early on can lead to better family relationships and more resilience.
- Promotes Early Communication Skills: Early detection allows speech and language therapists to begin communication treatments as soon as possible. Applied Behaviour Analysis (ABA) and augmentative and alternative communication (AAC) strategies for speech treatment can be introduced early. These therapies are designed to help children with ASD improve their expressive and receptive language abilities, allowing them to interact successfully with their family, friends, and carers. Individuals with ASD can express their needs, ideas, and feelings more effectively, lowering frustration and enhancing overall quality of life [21].
- Enhances Long-Term Independence: Early treatments boost not just immediate outcomes but also long-term independence. Individuals with ASD are better able to develop critical life skills if behavioural problems, social interactions, and cognitive development are addressed early in life. The foundation created during early treatments helps individuals to negotiate social settings, seek school, find jobs, and live more independently as they proceed through adolescence and into adulthood. Early identification and interventionenable people with ASD to live full lives and contribute effectively to society [22].

Early autism spectrum disorder identification is critical because it lays the groundwork for appropriate and targeted therapies, support assistance and educational accommodations. Individuals with autism can get the required help to fulfil their full potential if ASD is identified at an early age, resulting in enhanced quality of life and increased independence. Furthermore, assisting families from the beginning of their journey may considerably improve their capacity to negotiate the problems connected with autism, establishing a supportive and inclusive atmosphere for the afflicted individual.

3. DEEP LEARNING TECHNIQUES FOR EARLY DETECTION OF AUTISM DETECTION

Deep learning strategies for early identification of Autism Spectrum Disorder (ASD) entail the application of several complex algorithms to various sorts of data, such as medical scans, voice recordings, and behavioural patterns. These approaches can reveal subtle patterns and connections that human viewers may miss. Some of the important deep-learning approaches used in the early identification of ASD are as follows:

- Convolutional Neural Networks (CNNs): CNNs are frequently used for image analysis and recognition. CNNs are used to analyse medical images like as magnetic resonance imaging (MRI) scans and functional MRI (fMRI) data in the context of ASD identification. These networks are capable of detecting anatomical abnormalities or variations in brain areas linked to ASD. CNNs are excellent at collecting spatial patterns inside pictures, making them useful tools for identifying fine features in brain scans [23].
- Recurrent Neural Networks (RNNs): RNNs are deep learning models that specialise in sequential data processing. They are used to identify ASD by analysing speech patterns and social interactions. RNNs may discern minor signals and differences in voice intonation, rhythm, and syntax in audio recordings and speech samples, which may suggest communication issues associated with ASD. Understanding the dynamics of social interactions relies heavily on RNNs' capacity to grasp temporal relationships in data [24].
- Long Short-Term Memory Networks (LSTMs): LSTMs are RNNs that can detect long-term dependencies in sequential data. They are especially valuable for analysing time-series data pertaining to behaviour and communication. LSTMs may recognise complex patterns in behavioural sequences, assisting in the identification of repeated behaviours or unusual social interactions that are suggestive of ASD. LSTMs assist to a better understanding of the developmental

pathways associated with ASD by analysing behavioural patterns throughout time [25].

- Graph Neural Networks (GNNs): GNNs are built to analyse graph-structured data, making them ideal for analysing the brain's intricate networks. GNNs can represent connection patterns in brain areas in the context of ASD identification, allowing researchers to find abnormalities in neural networks linked with the illness. GNNs can discover minor variations in brain connectivity by depicting brain areas as nodes and their connections as edges, offering crucial insights into the neurological basis of ASD [26].
- Ensemble Learning: Using ensemble learning approaches, many models are combined to increase overall prediction accuracy. Different deep learning models, such as CNNs, RNNs, and LSTMs, can be merged into an ensemble in the context of ASD detection. Each model is trained to analyse certain sorts of data (for example, visuals, speech, and behaviour), and their combined predictions give a more complete and accurate assessment of ASD risk. Ensemble learning reduces individual model biases and improves the diagnostic process's resilience [27].
- Transfer Learning: Transfer learning is the process of using information gained from one activity to improve performance on a related but distinct job. Pre-trained deep learning models built for broad image recognition tasks may be fine-tuned on specialised ASD-related datasets for ASD identification. This method enables researchers to profit from model characteristics gained in larger contexts and adapt them to the intricacies of ASD diagnosis, even when data availability is restricted [28].

Researchers and clinicians can build more accurate, sensitive, and efficient methods for the early identification of Autism Spectrum Disorder by integrating various deep-learning approaches and adapting them to specific ASD-related data sources. These developments have the potential to have a considerable influence on early intervention efforts, therefore increasing the quality of life for people with ASD and their families.

4. PROPOSED TECHNIQUES FOR EARLY DETECTION OF AUTISM

The suggested Multimodal Deep Learning Fusion combines Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transfer Learning for the Early Detection of Autism Spectrum Disorder (ASD).

- Data Collection and Preprocessing: Collect a variety of datasets, such as structural MRI scans, speech pattern audio recordings, and behavioural data from social interactions. Preprocess the data to guarantee that deep learning models are homogenous and compatible.
- CNN for Image Analysis: To process structural MRI images, use CNNs. CNNs are adept at detecting spatial patterns in pictures. Train a CNN to detect small structural abnormalities in brain areas linked to ASD. The CNN learns to recognise complex brain patterns that may indicate ASD-related problems.
- RNN for Speech Pattern Analysis: To analyse audio recordings of speech patterns, use RNNs, especially Long Short-Term Memory networks (LSTMs). LSTMs excel at detecting temporal relationships in sequential data. Train an LSTM network to recognise abnormal speech patterns, such as changes in tone,rhythm, and syntax. These patterns are frequently symptomatic of ASD-related communication difficulties.
- Transfer Learning using Pretrained Models: Use pretrained CNN and LSTM models to benefit from transfer learning. For example, train a CNN on a big dataset (such as ImageNet) and then fine-tune it using ASD-specific structural MRI data. Similarly, train an LSTM on a large corpus of text and then fine-tune it on audio data linked to ASD speaking patterns. This strategy to transfer learning takes information from larger settings and adjusts it to the special peculiaritiesof ASD-related data.
- Multimodal Fusion using a Hybrid Model: Create a hybrid neural network architecture by combining features from the CNN and LSTM layers. Concatenate or integrate the collected features before passing them through further fully linked layers for multimodal fusion. The network learns to prioritise data from diverse modalities, allowing it to capture intricate links between anatomical brain variations and ASD-related speech patterns.
- Training and Validation: Train the hybrid model with the integrated dataset, making sure to include both structural MRI and speech-related characteristics in the training process. Use proper validation approaches to avoid overfitting and verify that the model generalises adequately to previously unknown data.
- Interpretability and Explainability: Methods for model interpretability and explainability should be included. Layer-wise Relevance Propagation (LRP) techniques may be used to see which parts of the MRI images and speech data contribute the most to the model's predictions. These visualisations help professionals grasp the underlying cause of the diagnosis.
- Continuous Learning and Feedback Loop: Implement a continuous learning system that allows the model to be adjusted as new data becomes available. Update the model on a regular basis based on clinician feedback to ensure that it remains relevant and accurate as our understanding of ASD grows.

This suggested strategy, which integrates CNNs, RNNs, and transfer learning, provides a comprehensive approach to early ASD identification, capturing both structural and behavioural characteristics. The incorporation of pretrained models and the synthesis of multimodal data improves the model's accuracy and efficacy, perhaps leading to earlier and more accurate diagnoses of Autism Spectrum Disorder.

4.1 ALGORITHM

Step 1: Data Collection and Preprocessing:

- Gather diverse datasets: structural MRI images, audio recordings, and behavioural data.
- Preprocess the data: normalize MRI images, extract spectrogram features from the audio, and preprocess behavioural data.

Step 2: Pretrained Model Initialization

- Initialize a pretrained CNN (e.g., VGG16) for MRI feature extraction.
- Initialize a pretrained LSTM (e.g., LSTM pretrained on text data) for audio feature extraction.

Step 3: Hybrid Model Architecture

- Design a hybrid model architecture.
- Input Layer 1: MRI Image Input to the CNN for featureextraction. Input Layer 2: Audio
- Spectrogram Input to the LSTM for feature extraction.
- CNN Layer: Extract features from MRI using the pre-trained CNN model.
- LSTM Layer: Extract features from audio using the pre-trained LSTM model.
- Fusion Layer: Concatenate or merge the features fromthe CNN and LSTM layers.
- Fully Connected Layers: Add dense layers for further feature refinement and learning multimodal relationships.
- Output Layer: Single output neuron with sigmoid activation for binary classification (ASD or non-ASD).

Step 4: Model Training:

- Compile the hybrid model with an appropriate loss function (e.g., binary cross-entropy) and optimizer (e.g., Adam).
- Train the model using the integrated and pre-processedmultimodal dataset.
- Utilize techniques such as dropout and batch normalization to prevent overfitting.

Step 5: Interpretability and Explain ability:

- Implement Layer-wise Relevance Propagation (LRP) orother interpretability methods to visualize important regions in MRI images and significant features in audiodata contributing to predictions.

Step 6: Model Evaluation:

- Evaluate the model's performance on a separate test dataset using metrics such as accuracy, precision, recall,and F1-score.
- Conduct cross-validation to ensure the model's robustness and generalization.

Step 7: Continuous Learning:

- Implement a continuous learning mechanism where themodel is periodically updated with new data.
- Regularly evaluate the model's performance and retrain it with new samples to adapt to evolving patterns in ASD data.

Step 8: Deployment and Clinical Validation:

- Deploy the trained model in a clinical setting under thesupervision of healthcare professionals.
- Validate the model's predictions against real-world patient data, gathering feedback from clinicians to refine the algorithm further.

5. RESULTS

5.1 Advantages of Proposed Algorithm

The proposed Multimodal Deep Learning Fusion technique for Autism Spectrum Disorder (ASD) early detection combining Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transfer Learning has various advantages:

- Comprehensive Analysis of Multimodal Data: The system incorporates many data sources, such as MRI scans, audio recordings, and behavioural data, to provide a comprehensive understanding of ASD-related phenomena. Thiscomplete method considers both structural and behavioural factors, resulting in more accurate and nuanced assessments.
- Leveraging Pretrained Models: The technique harnesses information obtained from large datasets (such as ImageNet) and adjusts it to ASD-specific data by using pre-trained CNN and LSTM models. This strategy to transfer learning improves the model's capacity to recognise subtle patterns, increasing accuracy and efficiency.
- Enhanced Sensitivity to ASD Signs: Thealgorithm's sensitivity to a wide variety of ASD indicators is ensured by the combination of CNNs for picture analysis and LSTMs for speech pattern analysis. CNNs excel at capturing spatial patterns in brain scans, whereas LSTMs excel at recognising temporal patterns in speech, ensuring a thorough examination of ASD-related characteristics.
- Multimodal Fusion for Deeper Insights: The use of a hybrid model to combine data from different modalities (images and audio) allows for a more in-depth investigation of intermodal interactions. The model learns to balance the value of various parameters, capturing complicated relationships between anatomical brain variations and ASD-related speech patterns.
- Interpretability and Explain ability: The approach employs interpretability techniques such as Layer-wise Relevance Propagation (LRP), which allows doctors to visualise and comprehend the characteristics that contribute to the model's predictions. This transparency boosts the algorithm's credibility, delivering useful information to medical practitioners.
- Continuous Learning and Adaptability: The architecture of the algorithm allows for continual learning, allowing it to adapt to new data and changing trends in ASD. Regular data updates ensure the model's relevance and performance, transforming it into a resilient and flexible tool for early ASD identification.

- Early and Accurate Diagnosis: The proposed approach promotes early and accurate diagnosis of ASD by integrating the capabilities of CNNs, LSTMs, and transfer learning. Early detection of ASD allows for prompt treatments, increasing outcomes and overall quality of life for persons with ASD and their family.
- Clinical Applicability and Practical Utility: The algorithm's architecture assures that it may be used in clinical settings, providing healthcare practitioners with practical value. Because of its integration of several data sources and innovative procedures, it is a helpful tool for doctors, assisting in early ASD diagnosis and intervention planning.

5.2 Comparison

Deep Learning Technique	Accuracy	Advantages
CNN (Convolutional Neural Networks)	90% +	Excellent for image analysis, capturing spatial patterns in brain scans. Pretrained models enhance feature extraction [29].
RNNs (Recurrent Neural Networks)	80%-90%	Captures temporal dependencies in data. Suitable for identifying repetitive behaviours and atypical social interactions.
LSTMs (Long Short-Term Memory Networks)	9 90%+	Effective in understanding developmental trajectories and predicting ASD progression [30].
GNNs (Graph Neural Networks)	80%-85%	Analyses graph-structured data, representing brain connectivity. Captures complex relationships in neural networks. Useful for identifying alterations in brain connectivity associated with ASD.
Ensemble Learning	90% +	Combines multiple models for improved accuracy and robustness. Reduces biases by aggregating predictions from diverse models [31].
Transfer Learning	90% +	Adapts features learned from broader datasets to ASD-related data. Enhances accuracy and efficiency, particularly with limited ASD-specific data.

6. LITERATURE REVIEW

Irena Voinsky et al. [32] Several ML-generated models based on RNA expression datasets obtained during our recently published RNA-seq study were presented as preliminary tools for ASD diagnosis. Two of the suggested models, using the random forest classifier, achieve an accuracy of 82% in discriminating children with ASD from children without ASD. Their proof-of-concept study requires modification and independent confirmation by studies with significantly larger cohorts of ASD and NT children, and it should thus be regarded as a starting point for developing more accurate ML- based tools. Eventually, such technologies might potentially give unbiased support for early ASD diagnosis.

Chongruo Wu et al. [33] built deep learning models for automated detection of clinically significant behaviours shown by newborns in a one-on-one interaction scenario with parents or professional doctors. They presented baseline findings of behaviour categorization using two methods: (1) an image-based model and (2) a model based on face behaviour characteristics. They attain 70% accuracy for smiling, 68% accuracy for looking at a face, 67% accuracy for looking at an item, and 53% accuracy for vocalisation. Second, they concentrated on ASD diagnosis prediction, using a feature selection process to identify the most significant statistical behavioural features and an over and under sampling process to mitigate class imbalance, before developing a baseline ML classifier with an accuracy of 82% for ASD diagnosis.

Erkan et al. [34] their study attempted to categorise ASD data in order to give a rapid, accessible, and simple approach to help early ASD identification. For children, adolescents, and adults, three ASD datasets are employed. We employed the k-Nearest Neighbours (kNN), Support Vector Machine (SVM), and Random Forests (RF) methods to categorise the ASD data. The data in our studies was randomly divided between training and test sets. To test the classification algorithms, sections of the data were chosen at random 100 times. The average values were used to evaluate the final findings. SVM and RF are proved to be useful approaches for ASD classification. For all of the datasets shown above, the RF technique categorised the data with a 100% accuracy.

Hamza Sharif et al. [35] a machine learning-based approach for automated identification of ASD utilising corpus callosum and intracranial brain volume characteristics was suggested. Their suggested framework not only produced high recognition accuracy but also decreased the complexity of the training machine learning model by focusing on elements that are most important in terms of discriminative capacities for ASD classification. Second, for benchmarking and validating the capabilities of deep learning on neuroimaging data analysis. They also demonstrated the outcomes of the transfer learning technique. They employed the pre-trained VGG16 model for ASD classification for this purpose.

Fanchao Meng et al. [36] sought to see if their eye movement patterns in connection to cartoon characters or actual people may be used to diagnose ASD youngsters. The data from eye-tracking experiments were organised using a three-level hierarchical framework that included individuals, events, and regions of interest. The flattened vectors and diagnostic information were employed as features and labels, while random forest was used as the feature selection tool and classifier. The influence of the most relevant characteristics was assessed using logistic regression. A total of 161 children (117 with ASD and 44 with TD) were recruited, with a mean age of 39.70 12.27 months. The model's overall accuracy, precision, and recall were 0.73, 0.73, and 0.75, respectively.

Shirajul Islam et al. [37] A machine learning technique was used to predict and discriminate between autistic and non-autistic children. First, they acquired as much data as possible from the surveillance side. They also set certain specific questions and attempted to discover the most accurate responses to all inquiries. Furthermore, supervised learning algorithms were used to determine if children had ASD symptoms. Among the algorithms used, KNN and Random Forest had the highest accuracy and speed of diagnosis. Above all, their ultimate objective was to develop an online application that can give a user with machine learning-based analysis to precisely diagnose autism at an early age.

7. CONCLUSION AND FUTURE SCOPE

Finally, deep learning techniques have shown enormous promise in terms of revolutionising the early identification of Autism Spectrum Disorder (ASD). Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), Graph Neural Networks (GNNs), ensemble learning, and transfer learning have all been used to improve our knowledge of ASD-related patterns. These approaches not only enhanced diagnostic accuracy but also gave vital insights into the intricate interaction of anatomical and behavioural characteristics linked with ASD. Early identification remains critical, providing the foundation for appropriate treatments and individualised support, which may have a tremendous impact on the lives of people with ASD and their families.

Deep learning algorithms have a bright and diverse future in the early identification of ASD. To begin, future research should concentrate on improving existing models and building innovative architectures capable of handling multimodal data with more accuracy and efficiency. Collaboration between computer scientists, neuroscientists, and clinicians is essential for incorporating the most recent advances in technology and therapeutic practices. Second, employing explainable AI approaches to improve the interpretability of deep learning models has enormous promise. Interpretable models not only increase clinician trust but also give vital insights into the decision-making process, allowing for more accurate diagnoses.

Furthermore, the combination of real-time data and wearable devices opens up an exciting new study area. Continuous monitoring via wearable devices might give useful longitudinal data that could be used to construct predictive models for ASD progression and treatment success. Furthermore, resolving ethical considerations, data privacy problems, and assuring diversity in training datasets are critical milestones in the growth of these approaches. Collaboration with varied groups and cultures is required to guarantee that these models are applicable and effective across different populations. Using natural language processing techniques with deep learning models should improve our knowledge of ASD's linguistic components, such as speech patterns, language development, and social communication. Collaboration between researchers and industry stakeholders can result in the creation of user-friendly technologies that empower clinicians and educators, making early ASD identification more accessible worldwide. In essence, the future of deep learning in early ASD detection lies not only in technological advances but also in fostering interdisciplinary collaborations and ethical considerations, resulting in a more inclusive and informed approach to neurodevelopmental disorder diagnostics and intervention strategies.

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