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Analysis and Detection of Autism Spectrum using hybrid models

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ABSTRACT –

The project was entitled with "Autism spectrum disorder (ASD)" is a complicated neurological developmental disorder that manifests itself in a variety of ways. This project investigates the multifaceted challenges inherent in the early and accurate diagnosis of Autism Spectrum Disorder (ASD), a complex neurodevelopmental condition characterized by social communication deficits and restricted, repetitive behaviors. Given the absence of a definitive biological marker, ASD diagnosis relies heavily on clinical observation, developmental history, and standardized behavioral assessments, as outlined in the DSM-5. This research addresses the critical issue of diagnostic delays, frequently extending beyond four years of age, despite the potential for identification as early as two. Such delays are exacerbated by limited access to specialized clinicians, particularly in underserved rural areas, and socioeconomic disparities that hinder timely intervention. A significant component of this study explores the ongoing search for objective neuro markers to enhance diagnostic precision and efficiency. We examine the current state of research into potential markers, including neurophysiological, behavioral, eye tracking, anatomical, functional brain imaging, and genetic indicators. Notably, we delve into the emerging field investigating the correlation between facial dysmorphologies and underlying neurological conditions, grounded in the principle of "the face predicts the brain." This approach seeks to identify discernible physical traits associated with ASD, potentially facilitating earlier detection. Ultimately, this project aims to contribute to the development of more reliable, accessible, and cost-effective diagnostic tools for ASD. By addressing the current limitations in diagnostic practices and exploring innovative neuro marker based approaches, we seek to improve early intervention strategies and optimize long-term outcomes for individuals with ASD.

I. INTRODUCTION –

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects communication, social interaction, and behaviour. Traditional diagnostic approaches rely on expert clinical evaluations, which are often time-consuming, subjective, and prone to inconsistencies. Given the importance of early diagnosis in improving the quality of life for individuals with ASD, there is a growing need for automated diagnostic tools that can provide quick and accurate assessments. Machine learning (ML) and deep learning (DL) techniques offer a promising avenue for enhancing ASD detection by analysing behavioural and diagnostic data more efficiently.Current diagnostic methods primarily involve behavioural assessments requiring extended observation periods, leading to potential delays in intervention. These delays are further exacerbated by the limited availability of specialized clinicians, particularly in underserved regions. Researchers are actively exploring computational tools to improve the accuracy and accessibility of ASD diagnosis. Existing systems, such as questionnaire-based assessments, often suffer from high false-positive rates, necessitating the integration of ML/DL models with structured datasets for improved precision.

Emerging research has also highlighted the potential of facial dysmorphology analysis in ASD detection. Studies indicate that children with ASD exhibit distinct facial features, such as a broader upper face and wider eyes, compared to neurotypical individuals. Advanced imaging technologies, including 3D facial scans, enable precise morphological analysis. However, traditional facial evaluation methods are labour-intensive and costly. ML-based models, particularly convolutional neural networks (CNNs), have demonstrated promising results in automating ASD classification from facial imagery, achieving high accuracy levels.This research explores the application of ML and DL methodologies to develop robust ASD detection systems capable of integrating structured and image-based data. By optimizing algorithms and assessing their performance through relevant metrics, this study aims to contribute to the advancement of objective, efficient, and accessible autism diagnosis.

II . LITERATURE REVIEW

Autism Spectrum Disorder (ASD) is a multifaceted neurodevelopmental condition characterized by challenges in social interaction, communication, and behaviour. Given its diverse manifestations, ASD diagnosis remains complex and time-intensive. Traditional diagnostic methods rely on expert evaluations, including structured interviews and behavioural observations. However, these assessments are inherently subjective and can lead to delayed diagnoses, particularly in underserved areas. The increasing prevalence of ASD has prompted extensive research into more efficient diagnostic approaches, particularly through the use of machine learning (ML) and deep learning (DL) techniques.

Traditional Diagnostic Approaches

Historically, ASD diagnosis has depended on clinician-administered tools such as the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview-Revised (ADI-R). While these tools have been effective, they are labour-intensive, require significant expertise, and can introduce biases. Additionally, reliance on expert evaluations can delay diagnosis and intervention, negatively impacting developmental outcomes. The demand for alternative diagnostic tools has fueled interest in computational methods that can improve accuracy and accessibility.

Role ole of Machine Learning in Autism Detection.

ML techniques have gained traction in ASD research due to their ability to process large datasets and identify hidden patterns. Algorithms such as Decision Trees, Support Vector Machines (SVM), and Neural Networks have been explored for ASD classification based on behavioral, genetic, and neuroimaging data. Studies indicate that ML models can achieve high classification accuracy, potentially reducing reliance on subjective clinical assessments. Integrating genetic markers with ML models has further improved predictive capabilities, allowing for more precise ASD identification.

The Importance of Hybrid Models

Hybrid models combining multiple ML techniques offer promising solutions to ASD detection challenges. Ensemble learning techniques enhance reliability by integrating various models to minimize biases and improve accuracy. Additionally, hybrid approaches can incorporate multiple data sources, including behavioral, genetic, and neuroimaging information, providing a comprehensive ASD assessment framework.

Advancements in Deep Learning Techniques

Deep learning (DL), a subset of ML, particularly Convolutional Neural Networks (CNNs), has shown significant potential in image and speech-based ASD detection. Research has revealed distinct facial features and speech anomalies in individuals with ASD, which DL models can recognize with high accuracy. Additionally, DL approaches have been applied to neuroimaging data (MRI/fMRI), identifying structural and connectivity differences in the brains of individuals with ASD.

Challenges in Computational ASD Diagnosis

Despite the promise of ML/DL, key challenges persist. Limited and non-diverse datasets can lead to model biases and poor generalizability across populations. Moreover, the “black box” nature of deep models reduces interpretability, making clinical integration more difficult. These limitations necessitate the development of more transparent and inclusive models.

III . PROBLEM STATEMENT

3.1 Existing System: The current diagnostic framework for Autism Spectrum Disorder (ASD) predominantly depends on clinician-led evaluations, standardized assessment instruments, and structured questionnaires. These methods are rooted in behavioral science and are designed to systematically identify developmental deviations typically associated with ASD. Two of the most widely recognized tools in this domain are the Autism Diagnostic Observation Schedule (ADOS) and the Modified Checklist for Autism in Toddlers (M-CHAT). These instruments, when administered by trained professionals, provide a foundational basis for ASD screening and diagnosis. Autism Diagnostic Observation Schedule (ADOS): ADOS is regarded as the gold standard for observational assessment in autism diagnosis. It is a semi-structured, standardized diagnostic tool that evaluates communication, social interaction, play, and imaginative use of materials through direct interaction with the child. The assessment involves a series of planned activities and tasks tailored to the individual’s age and language skills, allowing clinicians to observe behaviors relevant to the diagnosis of ASD. Despite its proven clinical reliability, ADOS is resource- intensive, requiring significant expertise, time, and specialized training for proper administration and interpretation. Consequently, the outcome of the evaluation can be influenced by the clinician’s subjective interpretation, potentially introducing variability in diagnostic conclusions [7, 10].

Limitations:

Despite the widespread use of these diagnostic methods, the existing system has notable drawbacks. The reliance on human intervention in assessments like ADOS and M-CHAT can lead to inconsistencies in results, as the accuracy of the diagnosis may vary based on the evaluator's expertise and experience. Furthermore, these assessments may not be easily accessible to individuals in remote or underserved areas, resulting in delays in diagnosis and intervention [11, 14].

Additionally, current machine learning-based approaches to autism detection have emerged as potential solutions to address these challenges. However, existing ML models are often limited by small datasets and a lack of standardization across different studies, which can hinder their effectiveness and generalizability [19,20].

As a result, there is a pressing need for the development of automated, scalable solutions that can enhance the diagnostic process for ASD, ultimately improving early detection and intervention strategies for affected individuals and their families. In summary, while the existing diagnostic system for autism provides valuable tools for assessment, it is hampered by subjectivity, variability, and accessibility issues. The integration of machine learning techniques presents an opportunity to overcome these limitations and improve the overall efficiency and accuracy of autism detection.

3.3 Proposed System: The proposed system introduces a robust, data-driven framework for the early and accurate diagnosis of Autism Spectrum Disorder (ASD), leveraging advanced Machine Learning (ML) and Deep Learning (DL) methodologies. This system is designed to overcome the limitations of traditional diagnostic practices by incorporating diverse data sources, automating analysis, and providing actionable insights to clinicians and caregivers. The key components of the system are outlined as follows:

Data Collection and Preprocessing

The system initiates its diagnostic workflow with the acquisition of diverse and multimodal data types. These include:

- Standardized clinical assessments (e.g., ADOS, M-CHAT)
- Behavioural observations
- Video recordings of child interactions
- Audio and speech samples

Preprocessing plays a vital role in preparing this data for analysis. It involves data cleaning, managing missing values, normalization of numerical features, and transformation of raw inputs into structured formats.

Feature Extraction

Following preprocessing, advanced computational techniques are employed to extract meaningful features from the input data:

- **Computer Vision** is utilized to analyse video data, identifying facial expressions, gaze patterns, and gestures.
- **Speech Processing** techniques extract prosodic and phonetic features such as pitch, tone, and speech rhythm from audio samples.
- Behavioural metrics obtained from clinical assessments are quantified and structured for model ingestion.

These extracted features form a comprehensive representation of each individual's behavioural and communicative profile, which serves as the input for the ML and DL models.

Machine Learning and Deep Learning Models

The core diagnostic engine of the system consists of a combination of traditional ML algorithms and advanced DL architectures:

- **Machine Learning Models** such as Support Vector Machines (SVM), Random Forest, and Logistic Regression are trained on labeled datasets to classify children as either at risk for ASD or not.
- **Deep Learning Models**, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are employed to learn complex, non-linear patterns in unstructured data (e.g., images, video, and audio).

The integration of ML and DL models allows the system to effectively handle both structured and unstructured data, providing a more holistic diagnostic capability.

Continuous Learning and Model Adaptation

To maintain relevance and effectiveness over time, the system incorporates a **continuous learning mechanism**:

- As new data becomes available, the models are retrained or fine-tuned to reflect current trends and research findings.
- This ensures that the system evolves with advancements in ASD diagnostics and retains high diagnostic performance.

IV . METHODOLOGY

The proposed methodology integrates machine learning (ML) and deep learning (DL) techniques for early and accurate detection of Autism Spectrum Disorder (ASD). The process is divided into several stages:

Dataset Description and Data Preprocessing:

1. Data Collection: Data was gathered from structured assessments such as ADOS and M-CHAT, supplemented with demographic and behavioural information, and in some cases, image data.
2. Data Preprocessing: This included cleaning (handling missing values and outliers), transformation (encoding categorical data), feature scaling (normalization/standardization), and dimensionality reduction using PCA and RFE.
3. Feature Extraction: Behavioral features (e.g., social interaction, eye contact) and, if used, visual features (from facial image data) were extracted for model input.influences the accuracy and efficiency of predictive models, thorough preprocessing is essential for the overall success of the system.

Model Selection

Logistic Regression: Logistic Regression is a linear classification algorithm primarily used for binary classification problems. It estimates the probability that a data point belongs to a specific class using the logistic (sigmoid) function. This model is interpretable and computationally efficient, making it ideal as a baseline model. It provides insight into the weightage or influence of each feature in the prediction process.

Support Vector Machine (SVM):

SVM is a supervised learning model that identifies the optimal hyperplane that separates data points into distinct classes with the maximum margin. It is particularly effective in high-dimensional spaces and is robust to overfitting, especially when using non-linear kernel functions such as the Radial Basis Function (RBF). SVM is suitable for structured data classification, such as ASD behavioral attributes.

Random Forest:

Random Forest is an ensemble learning method that constructs multiple decision trees and combines their outputs to improve classification accuracy and reduce overfitting. It operates through a process called "bagging," where subsets of data and features are randomly selected to train each tree. Random Forest also provides feature importance metrics, aiding interpretability in medical diagnostics.

Multilayer Perceptron (MLP):

The MLP is a type of artificial neural network composed of an input layer, one or more hidden layers, and an output layer. It uses backpropagation for training and can model complex, non-linear relationships in data. MLP is well-suited for structured data like questionnaires and behavioral assessments in ASD detection. Its flexibility in architecture allows for tuning to achieve optimal performance.

Convolutional Neural Networks (CNN)

CNNs are deep learning architectures specifically designed for image data processing. They consist of convolutional layers that automatically learn spatial hierarchies of features from input images. CNNs are effective for analyzing visual cues such as facial expressions, making them highly applicable in detecting ASD traits from facial imagery. They reduce the need for manual feature extraction and are capable of capturing subtle patterns.

MobileNet

MobileNet is a lightweight, efficient convolutional neural network architecture optimized for mobile and embedded vision applications. It uses depthwise separable convolutions to significantly reduce model size and computational cost while maintaining accuracy. MobileNet is particularly useful in real-time ASD detection on resource-constrained devices, offering portability and speed for practical deployment.

Model Evaluation

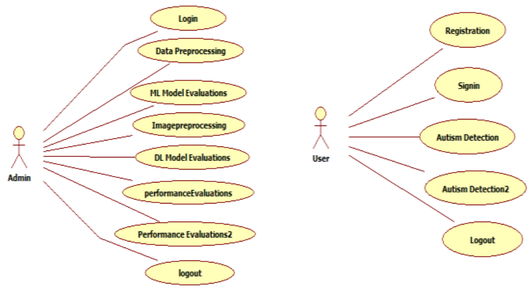
- **Accuracy:** Measures the overall correctness of predictions.
- **Precision:** Reflects the model's ability to correctly identify ASD cases without false positives.
- **Recall:** Indicates how well the model detects actual ASD cases (sensitivity).
- **F1-Score:** Harmonic mean of precision and recall to balance both metrics.

Testing and Prediction (GUI)Metrics:

To ensure the accessibility and practical applicability of the ASD detection system, a Graphical User Interface (GUI) was developed as a frontend layer for interacting with the backend models. This GUI allows clinicians, caregivers, or researchers to input behavioral attributes or upload facial image data for real-time analysis.

- **User-Friendly Interface**: The GUI was designed with a clean and intuitive layout, enabling non-technical users to enter assessment values (e.g., responses to behavioral questions) or upload images with ease.
- **Real-Time Feedback**: Upon data submission, the backend model processes the input and displays the prediction (e.g., "Positive for ASD" or "Negative for ASD") along with confidence scores.
- **Modular Functionality**: The system includes separate pages or tabs for user registration, login, data entry, image upload, and viewing predictions. Admin access also allows monitoring of user activity and data trends.
- **Output Visualization**: Graphical representations of model accuracy, precision, recall, and F1 score are included in the GUI for result interpretation. This aids in understanding model performance beyond simple classification.

V. EXPERIMENTAL RESULT



USE CASE DIAGRAM 1

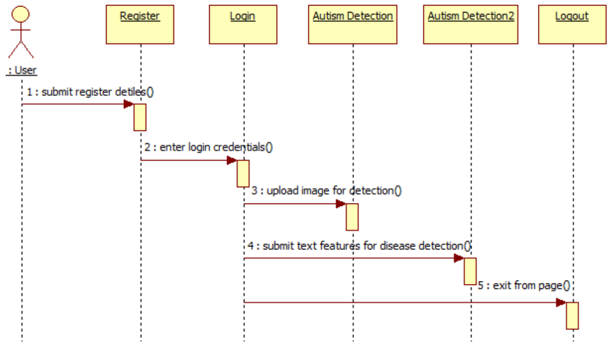


Fig2. Data flow diagram 1

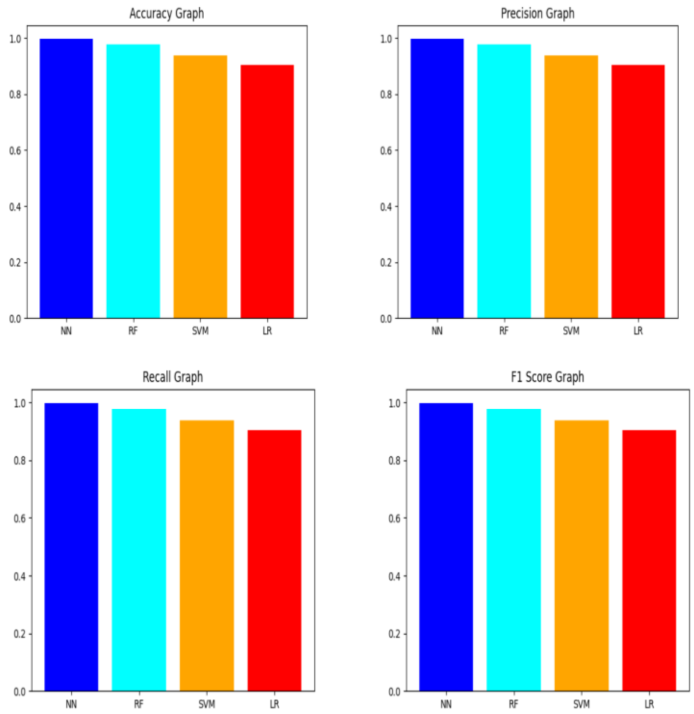


Fig3. Evaluation Gra

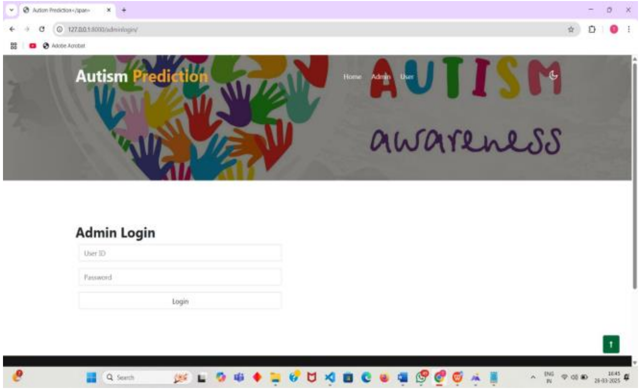


Fig4.Admin page

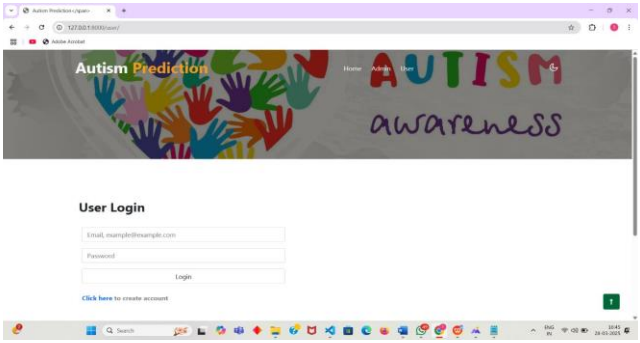


Fig5.UserPage

VI. CONCLUSION:

This research presents an intelligent and efficient framework for the early detection of Autism Spectrum Disorder (ASD) by leveraging both machine learning and deep learning methodologies. Through the integration of structured behavioral data and image-based features, the system demonstrates improved diagnostic accuracy, objectivity, and accessibility. Deep learning models, particularly CNN and MobileNet, exhibited strong performance in image classification, while traditional models like Random Forest were effective for structured data analysis. The deployment of a real-time, user-friendly GUI further enhances the practical applicability of the system. Collectively, this work contributes a scalable and cost-effective solution to aid in timely and accurate ASD screening and supports its integration into clinical and community-based settings.

VII. FUTURE WORK:

Autism Spectrum Detection System can focus on several key areas:

- **Integration of Multimodal Data**
  Future iterations of this work can incorporate additional data sources such as speech patterns, genetic markers, and neuroimaging (e.g., fMRI, EEG) to further enrich the model's predictive capabilities. Combining these with behavioral and visual data could provide a more holistic understanding of ASD indicators.

- **Larger and More Diverse Datasets**
  Expanding the dataset to include a more diverse population across different age groups, ethnic backgrounds, and geographical regions will improve the generalizability and fairness of the model. This can also help address potential biases in the training data.

- **Explainable AI (XAI) Integration**
  Enhancing model transparency through explainable AI techniques will increase trust among clinicians and caregivers. Providing interpretable insights into why a particular prediction was made can support informed decision-making in clinical environments.

- **Real-Time Deployment on Edge Devices**
  Optimizing the system for deployment on mobile or edge devices (e.g., smartphones or tablets) using lightweight models like MobileNet can facilitate real-time ASD screening in remote or underserved areas without the need for powerful computing infrastructure.
- **Continuous Learning and Model Updating**

Implementing mechanisms for continuous model learning based on new user data will enable adaptive performance improvement. This dynamic learning process ensures the system remains current with evolving diagnostic patterns and population characteristics.

- **Clinical Trials and Validation**
  Future work should involve extensive clinical validation of the system in real-world settings to assess its reliability, acceptance, and integration into existing healthcare workflows. Collaborations with healthcare professionals and institutions will be essential for this phase.

- **Personalized Intervention Recommendations**
  Beyond diagnosis, the system could be extended to suggest personalized intervention plans based on the severity and type of ASD traits identified, supporting tailored therapeutic strategies for each individual.

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