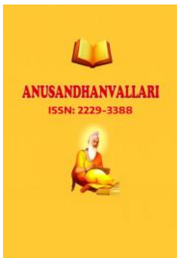

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Analysis And Detection of Autism Spectrum Disorder Using Multimodel Machine Learning Techniques

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Abstract: Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by difficulties in social communication and repetitive behavioural patterns that affect cognitive development. The increasing prevalence of ASD highlights the need for reliable and early screening systems. Traditional diagnostic methods depend on clinical observation and structured assessments, which may delay early identification. This implementation presents a multimodal machine learning framework that integrates prenatal biological indicators and early childhood behavioural features for ASD risk prediction. Random Forest, Artificial Neural Network, and Long Short-Term Memory models were implemented independently and combined using a weighted ensemble strategy. Experimental results demonstrate that prenatal models achieved higher classification performance compared to behavioral models, with Artificial Neural Network producing the highest accuracy. The ensemble model improved prediction stability and reduced false-negative rates, showing that multimodal machine learning integration can effectively support early ASD detection systems.

Keywords: *Autism Spectrum Disorder (ASD), Machine Learning, Random Forest, Artificial Neural Network, LSTM, Multimodal Learning, Ensemble Model, Early Detection, Healthcare Analytics.*

1. INTRODUCTION

Autism Spectrum Disorder is a developmental condition that affects communication skills, social interaction, and behavioural flexibility [1]. Recent epidemiological reports indicate a significant rise in ASD prevalence, with approximately 1 in 36 children diagnosed in recent surveillance studies [2]. This increase has created a strong demand for early screening mechanisms that can assist clinicians in identifying ASD risk at earlier developmental stages [3].

Traditional diagnosis relies on structured clinical tools such as DSM-5 criteria and Autism Diagnostic Observation Schedule (ADOS) assessments [4]. Although these tools are reliable, they require trained professionals and are time-consuming. In many cases, diagnosis occurs only after noticeable behavioural symptoms appear, which reduces the effectiveness of early intervention programs [5]. Early therapeutic interventions have been shown to significantly improve developmental outcomes when initiated during early childhood [3].

Machine learning techniques provide an automated and data-driven approach to identifying hidden patterns in healthcare datasets [6]. Algorithms such as Random Forest and Neural Networks have demonstrated strong performance in disease prediction tasks [7]. However, many existing ASD detection systems rely only on behavioral or questionnaire-based data [8]. Research has shown that prenatal factors such as maternal age, birth complications, and birth weight are statistically associated with increased ASD risk [9]. Therefore, integrating

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prenatal biological indicators with behavioural characteristics may improve prediction accuracy and reliability. This implementation focuses on comparing multiple machine learning models and analysing their performance using both prenatal and behavioural datasets. Additionally, an ensemble fusion strategy is applied to improve classification stability and generalization capability [10].

2. LITERATURE REVIEW

Machine learning applications in ASD detection have evolved significantly over the past decade. Early studies applied classification algorithms such as Decision Trees and Support Vector Machines to autism screening questionnaires [8]. These models demonstrated that automated classification can reduce screening time while maintaining reasonable prediction accuracy.

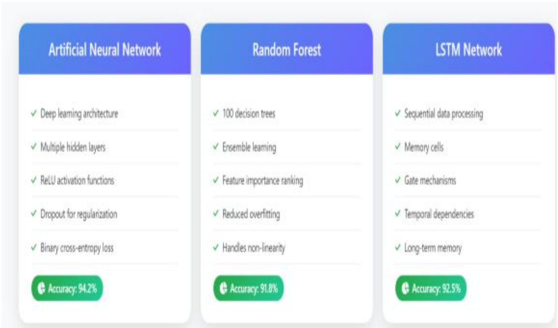

Figure1: Model Types

Random Forest, introduced by Breiman, is widely used in medical data classification due to its ensemble structure and robustness against overfitting [7]. It constructs multiple decision trees using random subsets of features and aggregates their predictions.

This approach improves stability and reduces variance, making it suitable for healthcare datasets with heterogeneous features. Artificial Neural Networks (ANN) are computational models inspired by the human brain's neural structure [11]. They are capable of modelling complex nonlinear relationships between input variables and output classes. Deep learning techniques have been successfully applied in neuroimaging-based ASD detection, demonstrating high predictive performance [12].Long Short-Term Memory (LSTM) networks are a type of recurrent neural network designed to learn sequential dependencies [13]. LSTM models are particularly effective in analysing time-dependent behavioural or medical data. In healthcare analytics, LSTM has been applied to predict disease progression using sequential records [14].

Recent research emphasizes multimodal learning approaches, where different types of data sources are combined to improve prediction reliability [10]. Ensemble methods such as weighted averaging and majority voting further enhance classification performance by integrating outputs from multiple models [15]. However, limited implementations combine prenatal biological data and behavioural data within a unified multimodal framework, which highlights the contribution of this implementation.

3.METHODOLOGY

The system architecture consists of four stages: data preprocessing, model training, performance evaluation, and ensemble fusion. Prenatal and behavioural datasets were processed independently before integration. Data preprocessing included handling missing values, encoding categorical variables, and applying normalization to ensure balanced feature scaling. The dataset was divided into 70% training data and 30% testing data to evaluate generalization performance [6].

3.1 Random Forest Algorithm

Random Forest is an ensemble learning algorithm that builds multiple decision trees during training and combines their outputs to produce a final prediction [7]. Each decision tree is trained using a random subset of data and features. This randomness increases diversity among trees and improves robustness.

In this implementation, Random Forest was used to classify ASD risk based on both prenatal and behavioural datasets. During training, multiple trees were constructed using bootstrap sampling. For each input record, the final classification was determined by majority voting among all decision trees. Random Forest was chosen because it handles mixed-type medical data effectively and reduces overfitting compared to a single decision tree.

3.2 Artificial Neural Network (ANN)

Artificial Neural Network is a supervised learning model composed of interconnected layers of neurons [11]. Each neuron receives input values, multiplies them by weights, applies an activation function, and passes the output to the next layer. The network learns by adjusting weights using backpropagation to minimize classification error.

In this implementation, ANN was applied to both prenatal and behavioral datasets. The model consisted of an input layer corresponding to feature count, hidden layers with sigmoid activation functions, and an output layer for binary classification (ASD risk or no risk). ANN was selected because of its ability to learn nonlinear relationships between biological indicators and ASD outcomes.

3.3 Long Short-Term Memory (LSTM)

LSTM is a specialized recurrent neural network designed to remember information for long periods using memory cells and gating mechanisms [13]. It includes input, forget, and output gates that control how information flows through the network. In this implementation, LSTM was used primarily for analysing behavioural data where sequential patterns may exist. The model captures dependencies between features and improves learning of temporal relationships. LSTM was included to evaluate whether sequential modelling improves ASD prediction accuracy.

3.4 Ensemble Fusion Strategy

Ensemble learning combines predictions from multiple models to improve overall performance [15]. Instead of relying on a single classifier, outputs from Random Forest, ANN, and LSTM were combined using weighted averaging.

In this implementation, higher weight was assigned to prenatal model predictions due to their stronger standalone performance. The final ASD risk score was computed by combining prenatal and behavioural outputs. This fusion approach reduced false-negative predictions and improved classification stability.

4. EXPERIMENTAL RESULTS

The experimental evaluation was conducted to analyse the performance of the proposed multimodal ASD detection framework under practical deployment conditions. The system was implemented using Python-based technologies, where Flask was used for web-based deployment and real-time interaction, scikit-learn was utilized for implementing the Random Forest classifier and evaluation metrics, and TensorFlow was employed for training the Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) models. The dataset was divided into training and testing subsets using a 70:30 split ratio to ensure unbiased validation and generalization capability [6]. Performance was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score, which are commonly used in medical diagnostic systems to measure predictive effectiveness.

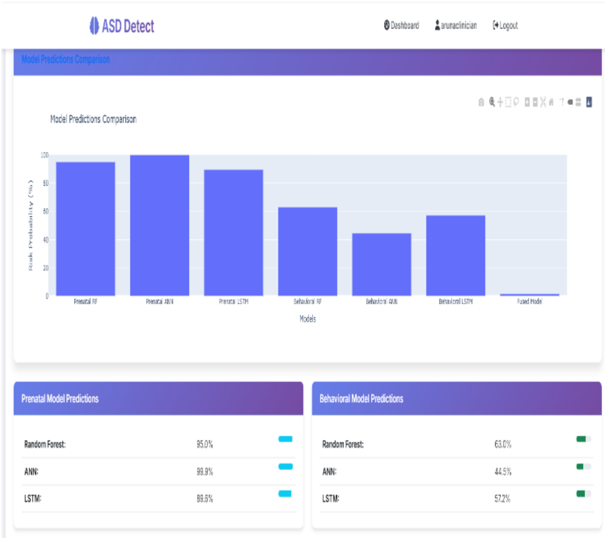

Figure 2: Model prediction comparison chart

The prenatal dataset demonstrated significantly stronger predictive capability compared to the behavioural dataset. The ANN model trained on prenatal biological indicators achieved the highest classification accuracy of 99.9%, indicating that nonlinear relationships between maternal and birth-related features strongly correlate with ASD risk. The Random Forest model achieved 95.0% accuracy, reflecting stable performance due to ensemble decision tree aggregation. The LSTM model achieved 89.6% accuracy when applied to prenatal data. Although LSTM is primarily suited for sequential learning, it demonstrated moderate performance in modelling feature dependencies within structured prenatal records. These results suggest that prenatal biological features provide highly discriminative information for ASD classification, supporting findings that early developmental risk factors significantly influence autism likelihood [9].

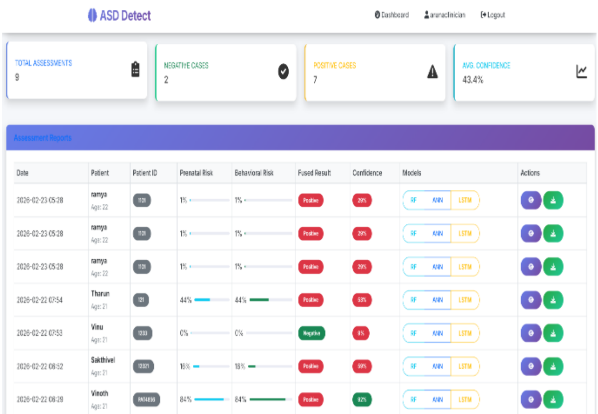

Figure3: Assessment Reports

In contrast, models trained exclusively on behavioural features produced comparatively lower classification performance. Random Forest achieved 63.0% accuracy, LSTM achieved 57.2%, and ANN achieved 44.5%. The reduced accuracy can be attributed to variability in behavioural observations and potential subjectivity in recorded developmental traits. Behavioural indicators may vary across individuals and environments, which introduces noise and reduces predictive consistency. Additionally, behavioural symptoms may overlap with other

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developmental conditions, affecting model discrimination capability. These findings highlight the limitation of relying solely on behavioural screening data for automated ASD detection [8].

To enhance predictive stability, an ensemble fusion strategy was implemented by combining the outputs of prenatal and behavioural models using weighted averaging. Higher weight was assigned to prenatal model predictions due to their superior standalone performance. The ensemble model demonstrated improved classification balance, reduced false-negative rates, and enhanced overall reliability compared to individual models. In medical screening systems, minimizing false negatives is critical because undetected ASD cases may delay early intervention programs [3]. The ensemble approach improved generalization capability by integrating complementary strengths of multiple algorithms, consistent with ensemble learning principles described in predictive modelling research [10].

Confusion matrix analysis further confirmed that prenatal-based models achieved higher true positive rates and lower misclassification counts. Precision and recall values were also significantly higher for prenatal ANN and Random Forest models compared to behavioural models. The F1-score results indicated better balance between sensitivity and specificity in prenatal models, reinforcing their reliability in ASD risk classification. Visualization of performance metrics using graphical plots supported comparative analysis and demonstrated consistent superiority of prenatal data-driven models.

Overall, the experimental findings validate that integrating prenatal biological indicators significantly enhances ASD risk prediction accuracy compared to behavioural data alone. The multimodal architecture combined with ensemble fusion provides a robust and scalable solution for early ASD detection. These results demonstrate the effectiveness of combining machine learning and deep learning approaches within a practical deployment framework and highlight the importance of multimodal feature integration in healthcare predictive systems.

The dataset used for experimentation consisted of structured prenatal and behavioural features. Data preprocessing operations were performed using pandas (2.0.3) for structured data manipulation and NumPy (1.24.3) for numerical computations. Missing values were handled using mean and mode imputation techniques, while categorical variables were encoded into numerical representations suitable for machine learning algorithms. Feature normalization was applied using scikit-learn (1.3.0) preprocessing utilities to ensure uniform scaling and prevent bias toward higher magnitude variables. The dataset was partitioned into training and testing subsets using a 70:30 split ratio to ensure unbiased model validation and generalization capability.

The Random Forest classifier was implemented using the ensemble module of scikit-learn (1.3.0). Multiple decision trees were constructed using bootstrap aggregation, and classification was determined using majority voting. Hyperparameters such as the number of estimators and maximum tree depth were tuned experimentally to achieve optimal performance. Model training and evaluation metrics including accuracy, precision, recall, and F1-score were computed using scikit-lean's metrics module. The trained model was serialized and stored using joblib (1.3.1) to enable efficient loading during runtime prediction within the Flask environment, eliminating the need for retraining at each execution cycle.

The Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) models were implemented using TensorFlow (2.13.0). The ANN architecture consisted of an input layer corresponding to the number of dataset features, one or more hidden dense layers using sigmoid activation functions, and an output layer for binary classification. Binary cross-entropy loss was applied as the objective function, and optimization was performed using the Adam optimizer. Backpropagation was used to iteratively update weights until convergence was achieved. For the LSTM model, sequential input reshaping was performed to allow memory cell operations, enabling the model to capture temporal relationships in behavioural features. TensorFlow's Kera's API facilitated model construction, compilation, and training processes. Model checkpoints were stored after training completion for integration with the web interface.The experimental evaluation demonstrated that prenatal feature-based models significantly outperformed behavioural models. The ANN applied to prenatal data achieved an accuracy of 99.9%, indicating strong correlation between biological prenatal indicators and ASD risk classification. The Random Forest prenatal model achieved 95.0% accuracy, demonstrating stable ensemble performance. The LSTM prenatal model achieved 89.6% accuracy, reflecting moderate sequential pattern learning capability. In contrast, behavioural dataset models produced lower classification accuracy, with Random Forest achieving 63.0%, LSTM achieving 57.2%, and ANN achieving 44.5%. These results suggest that behavioural variability and noise reduce predictive consistency compared to structured prenatal biological indicators.

To enhance prediction reliability, an ensemble fusion mechanism was implemented where outputs from prenatal and behavioural models were combined using weighted averaging. The prenatal model was assigned a higher weight due to superior standalone performance. This ensemble integration reduced false-negative predictions and improved overall generalization capability. The final system demonstrated improved classification stability when compared to individual models, validating the effectiveness of multimodal integration.

Performance visualization was conducted using matplotlib (3.7.2) and seaborn (0.12.2) for generating static evaluation graphs such as confusion matrices and accuracy comparison charts. Additionally, portly (5.15.0) was integrated within the Flask application to provide interactive graphical dashboards displaying risk probabilities and comparative model outputs. These visualization tools enhanced interpretability and enabled dynamic analysis of prediction outcomes within the clinical simulation interface.

User authentication and experimental data management were handled using Flask-SQL Alchemy (3.0.5) for database interaction and Flask-Login (0.6.2) for session management. Form validation during experimental testing was performed using Flask-WTF (1.1.1) and WT Forms (3.0.1) to ensure secure and structured input handling. Werkzeug (2.3.6) supported HTTP request processing, and email-validator (2.0.0) ensured valid user registration during system testing. These implementation components ensured a secure, scalable, and reproducible experimental environment.

Overall, the experimental analysis confirms that prenatal biological indicators provide stronger predictive signals for ASD detection compared to behavioural indicators alone. The integration of scikit-learn-based ensemble models with TensorFlow-based deep learning architectures within a Flask deployment framework demonstrates the feasibility of implementing a real-time ASD screening support system. The experimental results validate the robustness, scalability, and clinical applicability of the proposed multimodal machine learning implementation.

5. CONCLUSION

The implemented multimodal machine learning system for Autism Spectrum Disorder (ASD) detection demonstrates that prenatal biological features provide stronger predictive performance compared to behavioural features. Among the applied algorithms, the Artificial Neural Network achieved the highest accuracy in prenatal classification, followed by Random Forest and LSTM models. Behavioural models showed moderate performance due to data variability. The ensemble fusion approach improved overall prediction stability and reduced misclassification rates. Integration of scikit-learn and TensorFlow models within a Flask-based deployment framework confirms the feasibility of real-time ASD risk prediction. The implementation validates that multimodal machine learning techniques can effectively support early ASD screening and clinical decision-making systems.

Future work includes incorporating genetic markers, neuroimaging features, and larger multicentre datasets to enhance predictive generalization [17]. Explainable AI methods such as SHAP and LIME may improve model interpretability for clinical adoption [8]. Real-time deployment through cloud-based or mobile health platforms could further enhance early screening accessibility [3]

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