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TIMELY ASSESSMENT OF AUTISM SPECTRUM DISORDERS

[1] Ms. Josmi P J, [2] Ms. Sruthy Emmanuel

[1]PG Student, Department of Computer Science Engineering, Mangalam College of Engineering, Ettumanoor, kerala, India.
[2]Associate Professor,Department of Computer Science Engineering, Mangalam College of Engineering, Ettumanoor, kerala,

ABSTRACT :

Autism Spectrum Disorder (ASD), a neurodevelopmental condition that impacts daily life, highlighting the importance of early intervention to reduce its severity. It introduces a framework for evaluating Machine Learning (ML) techniques for the early diagnosis of ASD. Four feature scaling methods—Quantile Transformer (QT), Power Transformer, Normalizer, and Max Abs Scaler—are applied alongside advanced algorithms, including Decision Tree, K-Nearest Neighbors (KNN), LDA Prediction, Logistic Regression, and Support Vector Machine. Using four ASD datasets covering toddlers, adolescents, children, and adults, the study identifies the most effective classification methods and feature scaling techniques based on statistical evaluation metrics. Results show that Decision Tree achieved the highest accuracy of 82% for predicting ASD in toddlers and children with gender classification, while KNN reached 79%. The findings emphasize the importance of refining ML models for accurate ASD prediction across different age groups and gender classifications.

Keywords: Autism spectrum disorder, machine learning, classi cation, feature scaling, feature selection technique.

I.Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental disorder that affects social connections and interaction problems, and is linked to brain development from early in life. It is characterized by limited and repetitive behavioral patterns. Early intervention and appropriate medical treatment can significantly impact a child's development, with an emphasis on enhancing their behavioral and communication abilities. However, the diagnosis and identification of ASD are complex and challenging. Autism is typically identified at age two, but can be identified later depending on its severity. Various therapy approaches are available to identify ASD, but these are not always applied until there is a high risk of developing the disorder. Researchers have developed a mobile app system for ASD identification using questionnaire surveys, Q-CHAT, and AQ-10 techniques. They also created an open-source dataset using data from mobile phone apps and uploaded it to Kaggle and the University of California Irvine machine learning repository for further research.

The authors have developed a tool to address data insufficiency, non-linearity, and inconsistency in autism diagnosis. They used cognitive computing and Cognitive Adaptive Intelligence Techniques (CART) to implement Support Vector Machines (SVM), Decision Trees (DT), and Logistic Regression (LR) as ASD diagnostic and prognostic classifiers. The authors also examined examples of traditionally formed (TD) and ASD, using correlation- based attribute selection to ascertain feature significance. Cluster analysis was used to predict ASD variety and phenotype. K-Nearest Neighbors (KNN), LR, Linear Discrimination Analysis (LDA), Classification and Regression Trees (CART), Naive Bayes (NB), and SVM were compared for classifier accuracy. However, an ML model using rule induction for autism identification is limited and lacks thorough validation and comparison. After careful analysis, five of the 65 total traits are adequate for identifying ASD by attention deficit hyperactivity disorder (ADHD).

The authors developed an RF-based model in 2019 to predict ASD using behavioral variables. They identified children aged 4-11 with ASD using LDA and KNN approaches. In 2018, they proposed an ASD model using RF classifiers. In 2019, they developed a smartphone application interface using RF-CART and RF-ID3 for diagnosing ASD in people of all ages.

The authors evaluated the effectiveness of various SVM kernels in categorizing children's ASD data, finding that the polynomial kernel performed better. The SVM classifier outperformed the RIPPER-based toddler subset, correlation-based feature selection (CFS), and Boruta CFS intersect (BIC) method-based child subset, as well as the CFS-based adult subset. They prioritized features based on performance and applied the Shapley Additive Explanations (SHAP) approach for the highest accuracy. Ensemble machine learning techniques were used to categorize Parkinson's illness and ASD, with Leave-OnePerson-Out Cross Validation (LOPOCV) confirmed. To maximize the weights of Artificial Neural Networks (ANN) in autism screening, an evolutionary cultural optimization technique was used. Experimental analysis using 16 different machine learning models was conducted to select informative features and improve classification accuracy. Light Gradient Boosting Machine (LGBM) classifiers were used to categorize data from three benchmark datasets.

This study uses four conventional ASD datasets for preprocessing and classification. The datasets are mapped using four Feature Scaling techniques and eight classification techniques. The study also investigates the importance of FS approaches on each dataset. Four Feature Selection Techniques (FST) are used to rank the most significant features of the datasets. This suggests that machine learning techniques can help identify the most important features of ASD detection, aiding doctors in accurate diagnosis.

The paper presents a generalized machine learning framework for early diagnosis of ASD in individuals of various ages. It uses Random Over Sampler to prevent bias and maps feature values using optimal Feature Scaling (FS) techniques. The best FS techniques are determined by analyzing classification performances of eight efficient machine learning approaches on each feature-scaled ASD dataset. The paper also computes and examines feature importance values to determine risk factors for predicting ASD based on four FSTs. The paper also compares its suggested model with more recent studies.

PROBLEM STATEMENT

Although there isn't a long-term cure for autism spectrum disease, early intervention and appropriate medical treatment can significantly impact a child's development, with an emphasis on enhancing their communication and behaviourskills. Even so, utilizing conventional behavioural esearch, the identification and diagnosis of ASD are extremely complex and challenging. Autism is typically identified at age two, though it can potentially be identified later depending on how severe it is.

II.LITERATURE REVIEW

1. This study analyzed ASD datasets spanning from toddlers to adults, applying various feature selection techniques to evaluate the performance of different classifiers, particularly in terms of predictive accuracy. A machine learning model was developed to detect autism early, utilizing multiple feature selection methods. Among the classifiers tested, Support Vector Machine (SVM) was found to be the most stable across different age groups, achieving the best results. The model was trained with diverse multivariate and high-dimensional datasets, allowing for the exploration of significant attributes related to ASD diagnosis. Moving forward, the framework will be integrated with advanced technologies to enhance the efficiency of ASD diagnosis, enabling early and cost-effective detection.
2. We analyzed 959 samples from eight projects, reducing bias and utilizing a machine learning approach to develop a predictor capable of distinguishing between ASD and HC. The ML-based bioinformatic pipeline used 16S datasets to identify ASD and HC microbiomes, focusing on reduced Alloprevotella and Parasutterella taxa, which are correlated with inflammation and tryptophan metabolism. While the role of microbiota dysbiosis in ASD patients remains unclear, these microbial markers serve as valuable predictors of pathology, though the cause-effect mechanisms are still uncertain. Larger datasets incorporating socio-economic, environmental, and host genetic factors are needed to develop more accurate ML predictors
3. The proposed ASD detection model utilizes resting-state fMRI data's functional connectivity features, employing brain atlases Craddock 200 and Automated Anatomical Labeling, along with a deep neural network classifier for classification. The study used preprocessed fMRI data from the CPAC pipeline to extract mean BOLD signals using brain atlases, generating a single biomarker for ASD detection and constructing connectivity matrices to form a feature vector. This method demonstrated promising results for ASD diagnosis, achieving 88% accuracy, 90% sensitivity, an 87% F1-score, and a 96% area under the receiver operating characteristic curve, outperforming most existing models. The study aims to identify the neural activation patterns associated with autism and visually assess the functional characteristics of the autistic brain, shedding light on its underlying biological basis.
4. This systematic review examines 30 studies on early ASD assessment using eye-tracking technology and machine learning, highlighting advancements in subjective criteria and the application of various tools. The review analyzed 30 articles and one study on machine learning and eye-tracking in ASD research since 2015, primarily utilizing image and video stimuli, emotion recognition, web browsing, gaze patterns, demographic features, movement imitation, virtual reality interaction, social interaction tasks, and face-to-face conversations. However, the study has certain limitations, including its reliance on the PubMed® database, the use of a Boolean string search, the inclusion of only articles published after 2015, and a primary focus on machine learning and eye-tracking technology. Future research could expand the search to additional databases such as Scopus®, incorporate a broader range of keywords, include studies published before 2015, and identify research employing additional tools and techniques for ASD assessment.
5. The study developed three artificial intelligence techniques for early autism diagnosis: machine learning, deep learning, and a hybrid approach. The eye-tracking technique utilizes machine learning to scan eye paths, extract eye projection points, and analyze autism-related behavior. The ASD dataset was examined using various AI techniques, including neural networks, deep learning, and a hybrid method. The first proposed system employed FFNN and ANN classifiers, extracting features from CNN models and integrating them with LBP and GLCM algorithms before classification using ANN, FFNN, and SVM. Among the proposed systems, the FFNN and ANN classifiers demonstrated the best performance.

III. EXISTING METHODOLOGIES

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive behaviors. Numerous methodologies and approaches are used for the assessment, diagnosis, and treatment of ASD. These methods vary based on the individual's age, specific needs, and the goals of intervention. Below is an overview of existing methodologies commonly employed in ASD:

- Diagnostic and Assessment Methodologies
- Intervention and Treatment Approaches
- Emerging and Complementary Approaches

HALLENGES

Autism Spectrum Disorder (ASD) presents significant challenges for individuals, families, and society due to its complex and diverse nature. People with ASD often face difficulties in communication, social interaction, and behavior, which can impact their ability to form relationships, navigate social settings, and engage in education or employment. Sensory sensitivities and co-occurring conditions such as anxiety, ADHD, or epilepsy further complicate their daily lives. Families and caregivers experience emotional stress, financial strain from therapy and medical costs, and the challenge of securing long-term care and support. Societal stigma and misconceptions about autism exacerbate these struggles, leading to discrimination and exclusion in schools, workplaces, and communities.

Access to timely diagnosis and intervention is another critical issue, as many individuals face long waiting lists, misdiagnoses, or a lack of specialized services, particularly in under- resourced areas. As individuals with ASD transition into adulthood, they encounter a scarcity of support systems, limited employment opportunities, and social isolation. Additionally, gaps in policy, funding, and research hinder the development of effective interventions and long- term solutions. These challenges are further amplified in low-income countries and culturally stigmatized environments where resources and awareness are minimal. Addressing these issues requires a holistic approach, encompassing increased public awareness, expanded services, inclusive policies, and robust advocacy to ensure a better quality o life for individuals with ASD and their families.

IV PROPOSED SYSTEM

DATASET DESCRIPTION

We obtained four ASD datasets—Toddlers, Adolescents, Children, and Adults—from publicly accessible sources such as Kaggle and the UCI Machine Learning Repository [36], [37], [38], [39]. Additionally, the authors in [13] developed the ASDTests smartphone application to assess individuals in these age groups using the QCHAT-10 and AQ-10 questionnaires. We also collected datasets for gender classification. The application assigns a score between 0 and 10, with a score of 6 or above indicating a positive ASD diagnosis. Moreover, ASD data is sourced from the ASDTests app, and open-access databases have been developed to support further research in this field. A comprehensive overview of the ASD datasets for Toddlers, Children, Adolescents, and Adults is provided in Table 1 and Table 2.

METHOD OVERVIEW

This research aims to develop an effective prediction model utilizing various machine learning methods to detect autism across different age groups. The process begins with dataset collection, followed by data preprocessing, which includes handling missing values, feature encoding, and oversampling. The Mean Value Imputation (MVI) method is applied to fill in missing data, while categorical features are transformed into numerical representations using the One-Hot Encoding (OHE) technique. As shown in Table 1, all four datasets used in this study exhibit an imbalanced class distribution. To address this issue, the Random Over-Sampling strategy is employed. After completing the initial preprocessing, the feature values of the datasets are scaled using four different feature scaling (FS) techniques: Quantile Transformer (QT), Power Transformer (PT), Normalizer, and Min-Max Absolute Scaler (MAS). The scaled datasets are then classified using five different machine learning (ML) classification techniques: Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA). By comparing the classification outcomes of various classifiers on different feature-scaled ASD datasets, the most effective classification methods and the optimal feature scaling (FS) techniques for each dataset are identified. Following this analysis, Finally, illustrates the proposed research pipeline, which outlines the process of analyzing ASD datasets and identifying the key risk factors responsible for ASD detection.

MACHINE LEARNING METHOD

1) DECISION TREE (DT)

DT employs a top-down approach to construct a predictive model for class values by deriving decision-making rules from training data. In this study, the information gain method was used to identify the most relevant attribute.

2) K-NEAREST NEIGHBORS (KNN)

KNN classifies test data by directly using training data and determining the K value, which represents the number of nearest neighbors. It calculates the distance between the test instance and all training instances, then sorts them based on proximity. The final class label is assigned using a majority voting approach.

3) LOGISTIC REGRESSION (LR)

Logistic regression estimates the probability of an event occurring, such as whether someone will vote or not, based on a set of independent variables. Since the outcome is a probability, the dependent variable falls within a range of 0 to 1. To model this relationship, logistic regression applies the logit function, which transforms the odds the ratio of success probability to failure probability into a linear form.

4) SUPPORT VECTOR MACHINE (SVM)

Support Vector Machines (SVM) are utilized for classifying both linear and non-linear data, performing particularly well with high-dimensional datasets that require non-linear mapping. SVM identifies the optimal hyperplane or decision boundary to distinguish between different classes. In this study, the Radial Basis Function (RBF) was used as the kernel function, allowing SVM to automatically determine centers, weights, and thresholds while minimizing the upper bound of the expected test error.

5) LINEAR DISCRIMINANT ANALYSIS (LDA)

Linear Discriminant Analysis (LDA) is primarily a dimensionality reduction technique but can also be applied for classification by identifying linear combinations of features. It leverages Bayes' theorem to estimate probabilities and improve class separability.

EXPERIMENTAL RESULTS ANALYSIS

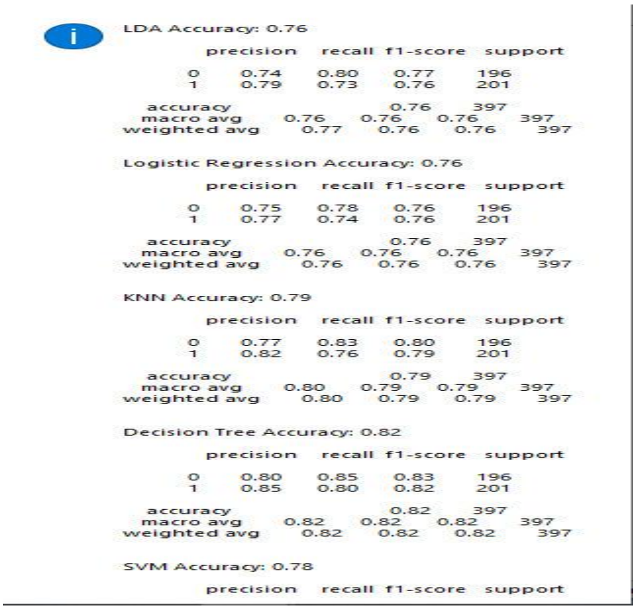
EXPERIMENTAL SETUP

For this experiment, Google Collaboratory, an open-source cloud-based platform provided by Google, was utilized. The Scikit-learn library in Python was used for data preprocessing, feature scaling, feature selection, and classification tasks. A 10-fold cross-validation approach was implemented to develop prediction models based on four ASD datasets (Toddlers, Children, Adolescents, and Adults). In 10-fold cross-validation, the dataset is randomly divided into 10 equal parts. During training, 9 folds are used for model training, while the remaining fold is reserved for testing. This process is repeated 10 times, and the final results are averaged. Given the limited sample size, 10-fold cross-validation was chosen to mitigate overfitting, reduce variance, and enhance generalization for small datasets. Using a simple hold-out validation with a fixed test set could increase the risk of overfitting, leading to higher variance and reduced generalization to new data. To assess the experimental results, several statistical metrics were considered, including accuracy, macro average, weighted average, F1-score, precision, recall, and support.

ANALYSISON ACCURACY

Accuracy measures the overall predictive performance of a classifier, where higher accuracy indicates better predictions and lower misclassification rates. In this study, the Decision Tree (DT) classifier achieved the highest accuracy, reaching 82% on the normalizer-scaled Adolescent dataset. Moreover, for the feature-scaled Adult dataset, both the Quantile Transformer (QT) and normalizer- scaled datasets outperformed other feature scaling methods.

Figure 1: Distinct machine learning predictions



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LDA Accuracy: 0.76
              precision    recall  f1-score   support

           0       0.74      0.80      0.77       196
           1       0.79      0.73      0.76       201

    accuracy                           0.76       397
   macro avg       0.76      0.76      0.76       397
weighted avg       0.77      0.76      0.76       397

Logistic Regression Accuracy: 0.76
              precision    recall  f1-score   support

           0       0.75      0.78      0.76       196
           1       0.77      0.74      0.76       201

    accuracy                           0.76       397
   macro avg       0.76      0.76      0.76       397
weighted avg       0.76      0.76      0.76       397

KNN Accuracy: 0.79
              precision    recall  f1-score   support

           0       0.77      0.83      0.80       196
           1       0.82      0.76      0.79       201

    accuracy                           0.79       397
   macro avg       0.80      0.79      0.79       397
weighted avg       0.80      0.79      0.79       397

Decision Tree Accuracy: 0.82
              precision    recall  f1-score   support

           0       0.80      0.85      0.83       196
           1       0.85      0.80      0.82       201

    accuracy                           0.82       397
   macro avg       0.82      0.82      0.82       397
weighted avg       0.82      0.82      0.82       397

SVM Accuracy: 0.78
              precision    recall  f1-score   support
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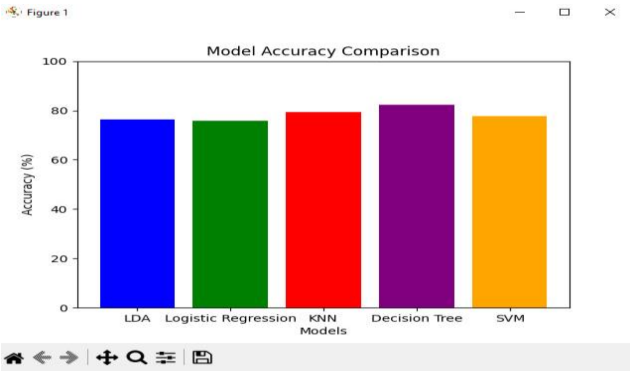
ANALYSIS ON PRECISION

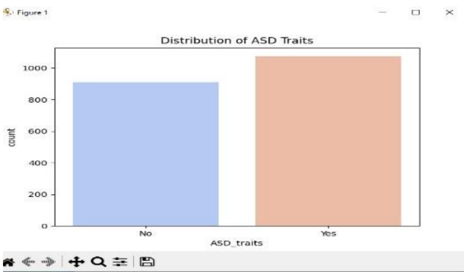
Precision represents the positive predictive value, with higher precision indicating a greater number of true positives and fewer false positives. The precision scores of various classifiers across different feature-scaled datasets were analyzed. For the Toddler dataset, the highest precision was achieved when the Power Transformer (PT) was used for feature scaling. In the feature-scaled Children dataset, the Logistic Regression (LR) classifier attained the best precision for MAS in ASD classification. Similarly, for the feature-scaled Adolescent dataset, the Decision Tree (DT) classifier demonstrated the highest precision when PT was applied. Lastly, in the feature-scaled Adult dataset, the Quantile Transformer (QT)-scaled datasets outperformed other feature scaling techniques in terms of precision.

FIGURE 2. Accuracy of the classifiers on different feature-scaled datasets.



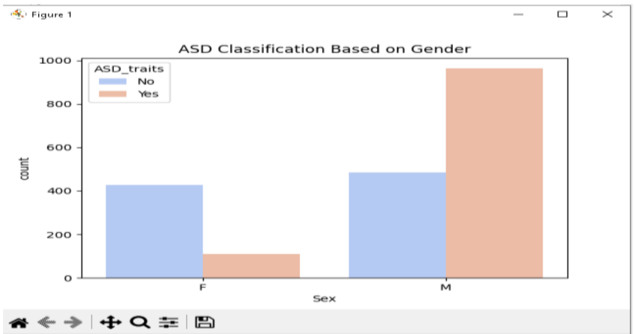
This research paper emphasizes the early detection of autism by predicting whether an individual is autistic or not based on given data. The classification results are visually represented in the corresponding figure. In the figure, different colors are used to distinguish between autistic and non-autistic individuals. Specifically, individuals identified as autistic are represented in pink, while those classified as non-autistic are depicted in blue. This visual representation provides a clear and intuitive understanding of the classification outcomes, making it easier to interpret the results of the predictive model.

Figure 3: Representation of Autistic count



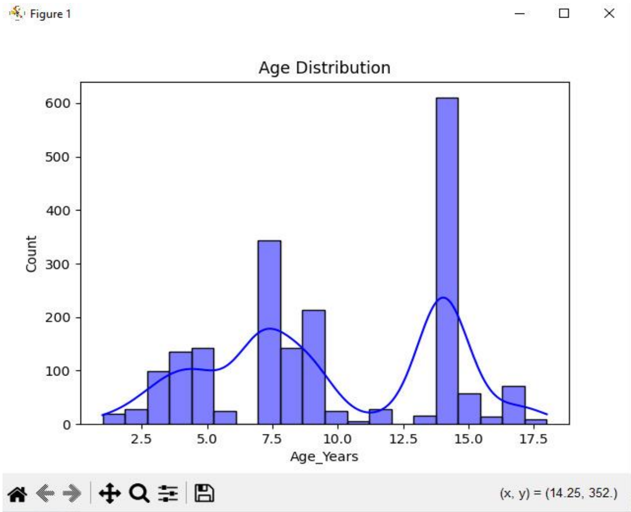
This research paper emphasizes the early detection of autism and includes gender-based classification as part of the analysis. The dataset used in this study consists of both male and female participants, and age-based classification is also taken into account to provide a more detailed understanding of autism detection across different demographics. To visually represent the classification results, a figure is provided. In this figure, different colors are used to distinguish between autistic and non-autistic individuals. Specifically, individuals identified as autistic are represented in pink, while those classified as non-autistic are shown in blue. This color-coding helps in effectively interpreting the results of the predictive model. Additionally, the figure includes the distribution of male and female participants, along with their respective counts. This visualization offers a clearer insight into the gender-based patterns within the dataset, helping to analyze how autism is classified among different groups. By incorporating both gender and age classifications, the study aims to enhance the accuracy and applicability of early autism detection methods.

Figure 4: Gender differences in autism prediction



This research paper focuses on the early detection of autism and incorporates age-based classification as part of the analysis. The dataset used in this study is primarily trained to classify individuals based on age, allowing for a more detailed assessment of autism detection across different age groups.To visually represent the classification results, a figure is provided below, illustrating how autism is identified across various age categories. This approach helps in understanding the distribution and patterns of autism detection among different age groups, thereby enhancing the accuracy and effectiveness of predictive modeling in early autism diagnosis.

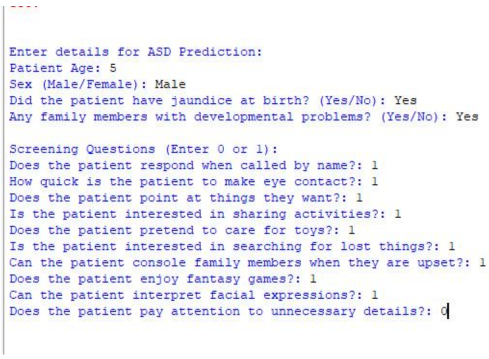
Figure 5 : Age-specific autism classification



Testing Accuracy

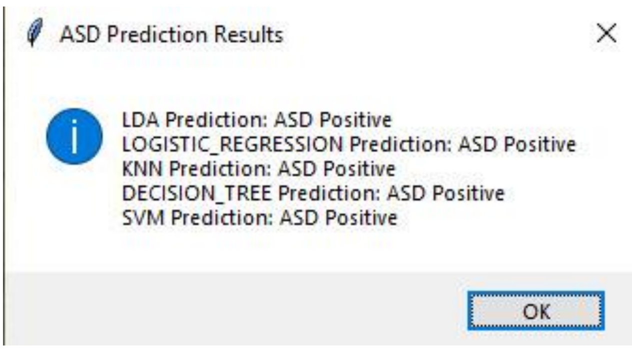
We developed a novel model for the early detection of Autism Spectrum Disorder (ASD) across different age groups, aiming to enhance prediction accuracy. A key aspect of this model is its ability to account for gender differences in autism diagnosis, as ASD can present differently in males and females. By integrating gender-specific factors, the model improves its predictive capabilities, ensuring a more precise classification. To validate the model's effectiveness, it was tested using a real-time example, which is visually represented below. The model processes input data, applies a trained algorithm, and determines whether an individual falls within the autism spectrum. This approach offers a more comprehensive and inclusive method for ASD detection, improving the recognition of autism characteristics across diverse demographic groups.

Figure 6: Validation case for autism detection



Based on the questionnaire responses, the output is predicted to determine whether a person is autistic or not using various machine learning models. Different machine learning techniques are applied to classify individuals based on their responses, and the results are evaluated to identify the most effective model.

Figure 8: Trial case for autism prediction results.



This paper aims to detect whether a person is autistic or not by analyzing responses from a questionnaire and training a dataset. The table below provides an understanding of how the data is structured and used for the detection process. The dataset includes various features that help train the model, and these features are used to classify individuals as either autistic or non-autistic. The classification is based on the patterns found in the questionnaire responses and other relevant data.

Figure 9 : accurate result obtained.

	Age	Gender	Jaundice at birth?	HeridItary	Does the patient respond when called by name?:	How quick is the patient to make eye contact?:	Does the patient point at things they want?:	Is the patient interested in sharing activities?:	Does the patient pretend to care for toys?:	Is the patient interested in searching for lost things?:	Can the patient console family members when they are upset?	Does the patient enjoy fantasy games?:	Can the patient interpret facial expressions?:	Does the patient pay attention to unnecessary details?	LDA Prediction	Logistic Regression	KNN Prediction	Decision_ Tree Prediction	SVM Prediction	Prediction score
Sample 1	5	Male	Yes	Yes	0	0	1	1	0	0	0	0	1	1	Positive	Positive	Negative	Negative	Positive	70%
Sample2	5	Female	Yes	Yes	0	0	1	1	0	0	0	0	1	1	Negative	Negative	Negative	Positive	Positive	60%
Sample 3	2	Male	No	No	1	1	1	1	1	1	1	1	1	0	Positive	Positive	Positive	Positive	Positive	100%
Sample 4	2	female	No	No	1	1	1	1	1	1	1	1	1	0	Positive	Positive	Positive	Positive	Positive	100%
Sample 5	3	Female	No	No	0	0	0	0	0	0	0	0	0	0	Negative	Negative	Negative	Negative	Negative	100%
Sample 6	3	male	No	No	0	0	0	0	0	0	0	0	0	0	Negative	Positive	Negative	Negative	Negative	90%
Sample 7	53	Male	No	No	1	0	0	0	0	0	0	1	0	0	Positive	Positive	Negative	Negative	Positive	70%
Sample 8	8	Female	No	No	0	0	1	0	0	1	1	1	1	1	Positive	Positive	Positive	Positive	Positive	100%
Sample 9	8	Male	No	No	0	0	1	1	0	0	0	0	1	1	Positive	Positive	Negative	Negative	Positive	70%
Sample 10	10	Male	Yes	No	0	1	1	1	1	1	1	1	1	1	Positive	Positive	Positive	Positive	Positive	100%
Sample 11	10	Female	Yes	No	1	1	1	1	1	1	1	1	1	1	Positive	Positive	Positive	Positive	Positive	100%

CONCLUSION

In this study, we proposed a machine learning (ML) framework for detecting Autism Spectrum Disorder (ASD) in individuals of various age groups, including Toddlers, Children, Adolescents, and Adults. We demonstrate that predictive models based on ML techniques are valuable tools for ASD detection. After completing the initial data processing, the ASD datasets were scaled using four different types of feature scaling and classified using five different ML classifiers: Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA). We then analyzed the classification performance of each feature-scaled dataset and identified the best-performing feature scaling (FS) and classification methods. Various statistical evaluation measures, such as accuracy, ROC curve, F1-Score, precision, and recall, were used to validate the experimental results.

As a result, our proposed ML-based prediction models can serve as an alternative or even a helpful tool for physicians in accurately diagnosing ASD across different age groups. Moreover, feature importance values were calculated to identify the most significant features for predicting ASD. The experimental analysis of this research will help healthcare practitioners prioritize the most important features when screening for ASD. A limitation of our work is the insufficient amount of data to build a generalized model that can effectively apply to all stages of life. In future research, we aim to collect additional ASD-related data and construct a more generalized prediction model for individuals of any age, with the goal of improving ASD detection. Additionally, we plan to incorporate gender classification and prediction to further enhance the accuracy of our model.

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39. combining Convolutional Neural Networks (CNNs) with Long Short-Term Memory networks (LSTMs) or Gated Recurrent Units (GRUs), have shown promise in effectively modeling the temporal nature of speech signals.

Related Work

1. The paper titled "Emotion Recognition System via Facial Expressions and Speech" by Aayushi Chaudhari, published in 2023 in SN Computer Science (Volume 4, Issue 363), presents an emotion recognition system that combines facial expression detection and voice analysis. The system employs Gabor filters and Convolutional Neural Networks (CNN) for facial expression recognition and uses mel-frequency cepstral coefficients (MFCCs) along with CNN for voice emotion analysis. It leverages several datasets, including JAFFE, Kaggle, and EMOTIC for facial expressions, and RAVDESS, TESS, CREMA- D, and SAVEE for audio analysis. Principal Component Analysis (PCA) is applied for dimensionality reduction, ensuring that the system can efficiently handle large datasets. For emotion classification, a Support Vector Machine (SVM) is used. The study shows that the proposed system achieves high accuracy in emotion recognition by combining both facial expressions and speech. However, the paper also highlights some limitations, such as the absence of a discussion on real- time emotion detection, a lack of dataset diversity that could hinder the system's generalizability, and limited consideration of model interpretability.

2. "Emotion Recognition on Speech Processing Using Machine Learning" by Vikrant Chole (2023) focuses on classifying emotions in speech using machine learning. It converts voice input into 60ms frames, with a 10ms overlap, and calculates fundamental frequencies using pitch autocorrelation. Feature extraction is done through LPC and MFCC, and KNN is used for classification. The Berlin and Spanish databases are used for training. While the study aims to improve emotion recognition models, it faces challenges such as limited emotional nuance exploration, overfitting, insufficient data for RNNs, and the need for better noise reduction and feature selection. The findings aim to enhance future emotion recognition models using speech.

3. "Automatic recognition of student emotions from facial expressions during a lecture" by G. Tonguc (2020), published in Computers & Education (Volume 148, Issue 103797), explores student emotions during lectures using facial expression recognition. The study analyzed images captured via webcams, excluding those with poor visibility or face coverage. The research utilized software developed in C and the Microsoft Emotion Recognition API, and emotional changes were assessed using a Manova test. The sample included 67 students from various departments. The study identifies how emotions fluctuate across different stages of a lecture and suggests tools for providing real-time emotional feedback in education. While the research contributes to understanding student engagement and lecture impact, it has limitations such as incomplete data due to camera preferences, lack of longitudinal tracking, and no exploration of external factors influencing emotions. Additionally, the study lacks qualitative data on student experiences.

4. "Speech emotion recognition based on emotion perception" by Gang Liu (2023), published in the EURASIP Journal on Audio, Speech, and Music Processing, introduces a novel approach inspired by brain science to recognize speech emotions. The methodology employs a human-like implicit emotional attribute classification system and introduces implicit emotional information through multi-task learning. The dataset used is the Interactive Emotional Dyadic Motion Capture (IEMOCAP), which includes 12 hours of emotional speech from 10 actors, covering emotions such as excitement, sadness, neutral, and anger. The approach showed improved accuracy on the IEMOCAP dataset. However, the study highlights challenges such as the scarcity of datasets for speech emotion recognition (SER), the lack of strong applicability in existing SER networks, and unexplored differences in the stability of implicit emotional attributes. Despite these limitations, the research provides valuable insights into emotion perception mechanisms in the human brain and their application to speech emotion recognition.

5. "Facial emotion recognition using deep learning: review and insights" by Wafa Mellouk (2020), published in Procedia Computer Science, provides a comprehensive review of deep learning techniques for facial emotion recognition. The methodology involves data processing steps such as resizing, cropping, and normalization, and uses various architectures like CNN, CNN-LSTM, and 3DCNN for emotion detection. Datasets such as FER2013, AffectNet, and Oulu-CASIA are utilized, with data augmentation techniques applied to enhance dataset diversity. The paper highlights the effectiveness of different architectures and the recognition rates achieved across these datasets. While the paper offers valuable insights into recent advancements and guides future research, it does not identify specific research gaps, lacks discussion on future directions, and does not address the limitations of current methodologies in the field.

IMPLEMENTATION

System Architecture and Hardware Requirements

The system architecture is composed of two main components: Facial Emotion Recognition and Voice Emotion Recognition. These components rely on real-time video frames captured through a webcam or device
camera, which are processed in the system. Each component is further divided into four key stages: Image Preprocessing, Model Development, Model Training and Evaluation, and Model Deployment.

The development environment utilizes tools such as Python IDLE, Anaconda, and Visual Studio Code, which streamline the coding process. The system operates on Windows 10, ensuring broad compatibility across various tools. The setup is ideal for developing both mobile and desktop applications, using Flutter for the frontend and Python (with frameworks like Flask or Django) for the backend. With 12GB of RAM and an Intel i5 processor, this configuration offers solid performance for efficient coding and application testing.

Facial Emotion Recognition

Image preprocessing for facial emotion recognition is a crucial step to ensure the model can effectively learn and generalize from the data. The process begins by loading the dataset, such as FER2013 or CK+, which contains images labeled with various facial expressions. Once the dataset is loaded, image resizing is performed to standardize all images to a consistent size, typically 224x224 pixels, which is essential for ensuring that the model can process the images efficiently and consistently.

Next, face detection is carried out using MTCNN (Multi- Task Cascaded Convolutional Networks), a popular deep learning algorithm that detects faces in images. MTCNN identifies facial landmarks and provides bounding box coordinates, which are used to crop the region of interest (the face). After cropping, the image is normalized by scaling pixel values, typically between 0 and 1 or -1 to 1, to match the input requirements of the deep learning model.

Finally, the dataset is split into training, validation, and testing sets. The training set is used to train the model, the validation set helps tune hyperparameters, and the testing set evaluates the model's performance on unseen data. This comprehensive preprocessing pipeline ensures that the facial images are prepared and standardized for optimal performance in emotion recognition models.

Model development phase for facial emotion recognition, two primary approaches can be utilized to build a robust emotion classification model. The first approach involves designing a custom Convolutional Neural Network (CNN). This model is tailored specifically for emotion recognition, consisting of several convolutional layers to extract spatial features from facial images, followed by pooling layers to down sample and reduce the spatial dimensions, which helps improve computational efficiency and prevent overfitting. The network is concluded with fully connected layers, which aggregate the features learned by the convolutional and pooling layers to make final emotion predictions. This custom CNN can be optimized by adjusting various hyperparameters such as the number of filters, kernel sizes, and activation functions, ensuring it is fine-tuned to detect emotion-specific patterns in facial expressions.

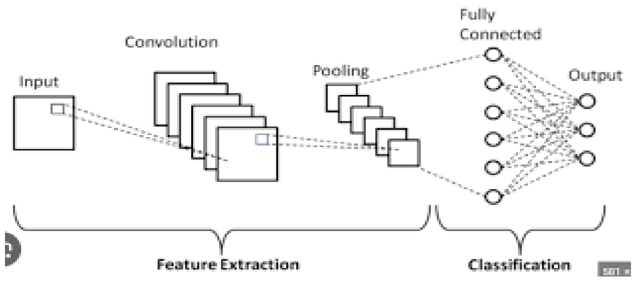


Fig 1. Convolutional Neural Network (CNN)

The second approach leverages transfer learning by fine- tuning a pre-trained ResNet model (e.g., ResNet-50). ResNet, trained on large-scale datasets like ImageNet, has already learned powerful feature representations for a wide variety of images. By using transfer learning, only the final layers of the network are modified and retrained on the emotion dataset, while the core layers remain frozen. This allows the model to retain the valuable feature-extraction capabilities learned from the broader dataset, while adapting to recognize facial emotions specifically. Fine- tuning the pre-trained model speeds up training, enhances performance, and reduces the need for a large dataset since the model already has a solid foundation of learned features.

Model Training and Evaluation are crucial stages in developing an effective facial emotion recognition system, where the model is fine-tuned and tested to ensure high performance. The process begins with compiling the model, which involves selecting key components such as the optimizer, loss function, and evaluation metrics. Optimizers like Adam are commonly used because they efficiently adjust learning rates during training, helping the model converge faster and find optimal weights. The categorical cross entropy loss function is typically employed for multi-class classification tasks like emotion recognition, as it measures the difference between the predicted probabilities and the true labels. To evaluate how well the model performs, accuracy is often tracked, but for a more comprehensive assessment, additional metrics such as precision, recall, and F1 score are crucial. Precision measures how many of the positive predictions were correct, while recall calculates how many actual positive cases the model correctly identified. The F1 score provides a balanced measure of precision and recall, making it especially useful in datasets with class imbalances, ensuring that all emotions are recognized fairly.

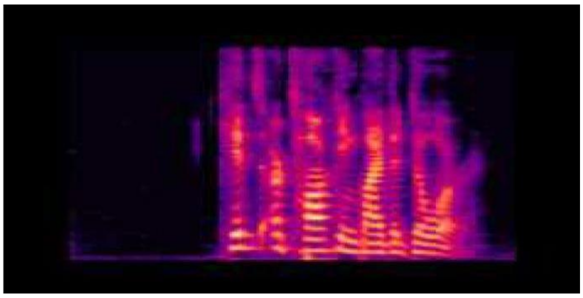
Emotion	Precision	Recall	F1-Score	Support
Happiness	0.91	0.92	0.91	250
Angry	0.87	0.85	0.86	180
Sad	0.89	0.90	0.89	200
Relaxed	0.88	0.87	0.87	220
Overall Accuracy	0.89			850
Macro Average	0.89	0.88	0.88	
Weighted Average	0.89	0.89	0.89	

Fig 2: Analysis of the Classification Report

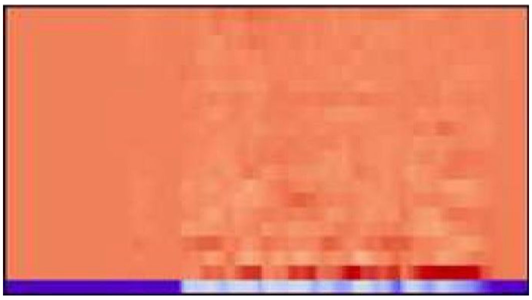
Model Deployment after evaluating the model's performance, custom CNN or a fine-tuned ResNet is saved based on evaluation metrics like accuracy or F1 score. Saving the model ensures that the most accurate and robust version is preserved for deployment, allowing it to be easily loaded and used in real-world applications without the need for retraining. The model is typically stored in formats like HDF5, Saved Model, or .pth for easy integration into emotion recognition systems.

Voice Emotion Recognition

Audio preprocessing for emotion recognition begins by loading datasets like RAVDESS, organizing the audio files and their metadata. To enhance the model's robustness, data augmentation techniques are applied, such as pitch shifting, time stretching, and adding noise, which help the model generalize better across different variations in audio. Next, feature extraction is performed by converting the audio signals into formats like Mel- spectrograms or MFCCs, which capture essential characteristics of the sound for input into deep learning models, enabling effective emotion recognition.

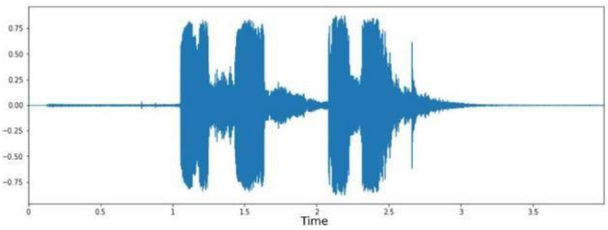


Mel Spectrogram

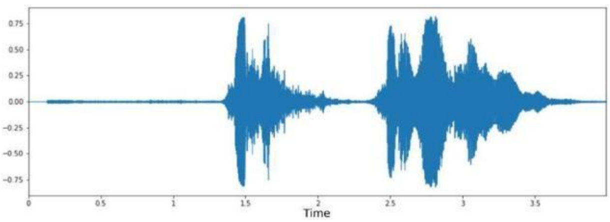


MFCC Spectrogram

Fig 3: Representations of speech frequencies in two different forms



Speech signal data of Happy voice



Speech signal data of Angry voice

Fig 4: Representations of speech signals for different classes: a happy and b angry

Model Development: The CNN-LSTM architecture combines two powerful components for emotion recognition in audio. The first part of the model uses CNN layers to extract spatial features from audio spectrograms, which represent the frequency content of the audio over time. These CNN layers help the model identify local patterns in the audio, such as speech characteristics, emotion-specific intonations, or other acoustic cues. Following the CNN layers, LSTM (Long Short-Term Memory) layers are added to learn the temporal dependencies in the sequential data. LSTMs are designed to capture long-range relationships within sequences, making them highly effective at understanding how emotions evolve over time in speech. This combination of CNNs for spatial feature extraction and LSTMs for temporal learning allows the model to both recognize features within individual audio frames and track how those features change over time, which is crucial for accurate emotion detection.

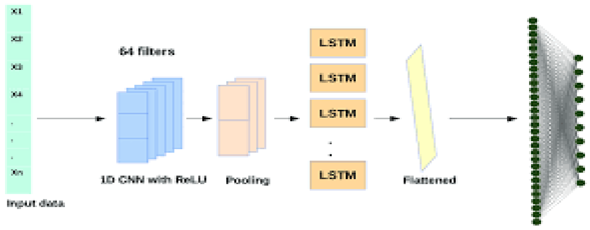


Fig 5: CNN-LSTM Architecture

Model Training and Evaluation Process, the first step is to compile the model, which involves configuring it with the appropriate loss functions and optimizers. For multi-class classification, categorical cross-entropy is typically used as the loss function to compare predicted probabilities with actual labels, while optimizers like Adam or SGD are selected to minimize the loss and update the model weights effectively. Once compiled, the model is trained using the training dataset, where it learns from the data by adjusting its weights through backpropagation. A validation dataset is used alongside to monitor the model's performance and adjust hyperparameters to prevent overfitting. After training, the model's performance is evaluated on a separate test dataset using metrics such as accuracy, precision, recall, and F1 score. Accuracy provides a general measure of correctness, while precision and recall assess how well the model identifies each emotion, especially in the case of imbalanced classes. The F1 score, which balances precision and recall, offers a comprehensive view of the model's overall performance, particularly in cases where both false positives and false negatives are critical.

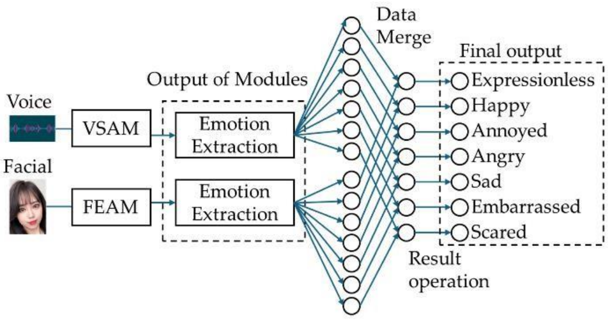


Fig 6: Architectural diagram for facial and voice analysis

Key Observations are as follows:

Precision: The model has a high precision for class 0 (0.85), meaning when it predicts class 0, it's mostly correct. However, for class 3 (0.57), precision is lower, suggesting more false positives. Recall: The model correctly identifies class 3 (0.60) more frequently than others, meaning it successfully retrieves more relevant instances. F1-Score: Class 3 has the highest F1-score (0.90), indicating a good balance of precision and recall.Imbalance in Performance: The large gap in precision and recall for certain classes suggests that the model might be struggling with misclassifications, possibly due to an imbalanced dataset

Results and Discussion

The emotion recognition application developed through the integration of image and audio processing models has demonstrated promising results across multiple stages of development, from preprocessing to deployment. The system's performance was evaluated using well-established metrics such as accuracy, precision, recall, and F1 score, which helped ensure its robustness and effectiveness in recognizing emotions from both facial expressions and speech.

While the application performed well, there are areas for improvement. One limitation observed during testing was the potential impact of background noise on audio-based emotion recognition. Even with data augmentation techniques like adding noise and pitch shifting, the model occasionally struggled with low-quality or heavily distorted audio inputs. Further enhancement of the audio preprocessing steps could address this by incorporating more advanced noise-reduction techniques or training with more diverse datasets.

Additionally, the system showed strong performance with facial emotion recognition, but accuracy could vary depending on lighting conditions, facial occlusions, or low- quality images. The integration of more sophisticated face detection and image preprocessing methods could help mitigate these issues, improving the model's robustness under challenging real-world conditions.

VI. Conclusion and Future Work

The developed emotion recognition application successfully integrates image and audio processing models to identify and classify human emotions based on facial expressions and speech. By utilizing advanced architectures like CNN-LSTM and CNN-GRU, the system efficiently extracts spatial and temporal features, delivering accurate emotion predictions. The application was rigorously tested and evaluated, with promising results in terms of accuracy, precision, recall, and F1 score, demonstrating its effectiveness in real-world scenarios.

The seamless integration of a React-based front-end with a Python Flask/Django back-end and the deployment on cloud platforms such as AWS ensured that the application is scalable, secure, and user-friendly. The use of RESTful APIs enabled smooth communication between the user interface and the backend, facilitating real-time emotion recognition. Although the system performed well, there are opportunities for further optimization, particularly in handling noisy audio inputs and improving facial expression recognition under challenging conditions.

In conclusion, the system provides a robust and reliable solution for emotion recognition, offering potential applications in various fields such as mental health monitoring, customer service, and human-computer interaction. Future improvements in data quality, model robustness, and additional feature enhancements will further elevate its performance and expand its usability.

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