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Performance Evaluation of ML and DL Approaches For Early Diagnosis of Autism Spectrum Disorder and Development of Autistic Care Hub

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AGENDA

- **Abstract**
- **Introduction**
- **Motivation**
- **Literature Survey**
- **Proposed Approach**
- **Results and Discussion**
- **Conclusions**
- **References**

Abstract

- ASD is a neurodevelopmental disorder affecting social interaction, communication, and behavior, with early diagnosis being key to better outcomes.
- This work compares ML (KNN, SVM, Decision Tree, Random Forest, XGBoost, Logistic Regression), unsupervised clustering (K-Means, Agglomerative, Spectral, GMM, BIRCH), and DL models (Dense, LSTM, Residual connections) for early ASD detection using AQ-10 data. Feature selection shows behavioral markers as stronger predictors than demographics.
- Results highlight the superior performance of ensemble ML and DL models, with the best integrated into the *Autism Care Hub* for screening, diagnosis, and monitoring

Introduction

- **Autism (ASD)** is a neurodevelopmental condition affecting social interaction, communication, and behavior, and spans all IQ levels and varying abilities.

- It can be analyzed using various **Machine Learning (ML)** and **Deep Learning (DL)** algorithms to find a better model for predicting autism.

Motivation

- **Autism Spectrum Disorders (ASD)** are a diverse group of neurodevelopmental conditions that affect behavior, communication, and social interaction.

- **Prevalence and Diagnosis:** About 1 in 100 children has autism. Although signs may appear in early childhood, diagnosis is often delayed.

- **Variation in Needs:** The abilities and needs of autistic individuals vary widely—some can live independently, while others may have severe disabilities requiring lifelong care and support.

Literature Survey

SNO	PAPER TITLE	SUMMARY	APPROACH
1.	An evaluation of machine learning approaches for early diagnosis of autism spectrum disorder Rownak Ara Rasul a, Promy Saha b, Diponkor Bala c,∗, S.M. Rakib Ul Karim d, Md. Ibrahim Abdullah a, Bishwajit Saha e[1]	● For children: A4 (difficulty understanding emotions) was key. ● For adults: A9 (aversion to physical contact) was significant. ● ML enables faster, more accurate ASD diagnosis. ● Key traits: Emotional difficulty (children), aversion to contact (adults). ● Developed a GUI for easy clinician use. ● Future focus: Larger datasets and deep learning.	The study demonstrates that machine learning models, particularly SVM, LR, and ANN, can effectively aid in the early diagnosis of ASD. The integration of clustering algorithms provides additional insights, especially in scenarios lacking labeled data. The research underscores the potential of machine learning in developing cost-effective and efficient diagnostic tools for ASD

S.NO	PAPER TITLE	SUMMARY	APPROACH
2.	Applications of Supervised Machine Learning in Autism Spectrum Disorder Research: a Review.Kayleigh K. Hyde1 & Marlena N. Novack2 & Nicholas LaHaye1 & Chelsea Parlett-Pelleriti1 & Raymond Anden1 & Dennis R. Dixon2 & Erik Linstead1[2]	● Growing ML Adoption: Supervised ML is widely used in ASD research, improving diagnosis, genetics understanding, and interventions using large datasets. ● Promising Algorithms: Tools like SVM and ADTree enhance diagnostic accuracy and identify ASD biomarkers from behavioral, neuroimaging, and genetic data. ● Challenges: Model complexity and lack of diverse datasets remain major hurdles.	● ML Algorithms: SVM, ADTree, Random Forests, and neural networks were used to improve diagnosis and find ASD biomarkers

S.NO	PAPER TITLE	SUMMARY	APPROACH
3.	A Systematic Literature Review on the Application of Machine-Learning Models in Behavioral Assessment of Autism Spectrum Disorder by Nadire CavusAbdulmalik A. Lawan,Zurki Ibrahim,Abdullahi Dahiru,Sadiya Tahir,Usama Ishaq Abdulrazak,Adamu Hussaini[3]	● The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was utilized in the paper to guide the systematic literature review process. ● ML models show promising evaluation metrics but lack real-life clinical application. ● Data discrepancies and misalignment with clinical diagnostic criteria. ● Conclusion: Future research should focus on aligning ML techniques with clinical practices for effective ASD assessment.	Assements tools: ADI-R, ADOS ML algorithms: SVM,RF,ANN,KNN,ADTREE,LR,NB, BayesNet,Adaboost, RIDOR, Metrics: Accuracy,Sensitivity, Specificity,F1

S.NO	PAPER TITLE	SUMMARY	APPROACH
4.	T. Zhang, R. Ramakrishnan, M. Livny,BIRCH: an efficient data clustering method for very large databases, ACM SIGMOD Rec. 25 (2) (1996) 103–114.[4]	• BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies) is a clustering algorithm designed for large datasets and incrementally clusters multi-dimensional data, optimizing memory and time & achieve good clustering with a single data scan and effectively handles noise. • Performance evaluations show BIRCH outperforms CLARANS in speed, quality, and order sensitivity. • The algorithm utilizes a height balanced CF tree for efficient data representation and clustering decisions	• Approaches in BIRCH: Probability-based approaches, Distance-based approaches,Incremental Clustering,CLARANS, Focusing techniques,Heuristic approaches

S.NO	PAPER TITLE	SUMMARY	APPROACH
5.	Machine Learning-Based Autism Screening Tool — A Modified Approach[5]	This paper proposes a modified machine learning (ML) approach to enhance the accuracy and efficiency of autism screening tools. The study focuses on developing predictive models using behavioral and questionnaire data, aimed at early detection of Autism Spectrum Disorder (ASD).	Modification: Ensemble methods and hyperparameter tuning were applied to improve prediction accuracy. Evaluation Metrics: Accuracy, precision, recall, and F1-score. Outcome: Modified ML approach showed improved diagnostic accuracy and reduced false positives.

S.NO	PAPER TITLE	SUMMARY	APPROACH
6.	Development and Validation of DSM-5 Based Diagnostic Tool for Children with Autism Spectrum Disorder[6]	● This paper describes the development and validation of a diagnostic tool grounded in DSM-5 criteria to assess ASD in children. It aims to align clinical diagnosis with standardized psychiatric guidelines.	Validation: ● Psychometric Testing: Reliability and validity checks including internal consistency (Cronbach's alpha), inter-rater reliability, and test-retest reliability. ● Clinical Comparison: Tool results were compared with gold-standard diagnostic assessments like ADOS and clinical judgment. ● Outcome: The tool demonstrated strong reliability and validity, making it suitable for use in clinical and research settings.

S.NO	PAPER TITLE	SUMMARY	APPROACH
7.	Autism AI: a New Autism Screening System Based on Artificial Intelligence Seyed Reza Shahamiri1 C Fadi Thabtah2	● Objective: Evaluate existing ASD screening methods and explore machine learning applications for improved detection. ● Conventional Methods: Discusses tools like CHAT and AQ, noting their limitations in sensitivity and specificity. Machine Learning: Highlights studies utilizing algorithms for autism detection, showcasing advancements in accuracy ● Conclusion: Identifies the need for integrating machine learning to enhance traditional screening approaches and improve diagnosis outcomes.	● Deep Learning Algorithm: Using Convolutional Neural Networks to predict autistic traits ● Automated Analysis The app processes the collected data via a web service that validates inputs and utilizes the CNN for accurate predictions, replacing traditional scoring methods.

Proposed Approach

DATASET DESCRIPTION

A1–A10 scores: 1(YES)/ 0(NO) based on the question asked in screening.

Feature no.	Attributes	Description
10	A1 score	The answer code of: Does the person speak very little and give unrelated answers to questions?
11	A2 score	The answer code of: Does the person not respond to their name or avoid eye contact?
12	A3 score	The answer code of: Does the person not engage in games of pretend with other children?
13	A4 score	The answer code of: Does the person struggle to understand other people's feelings?
14	A5 score	The answer code of: Is the person easily upset by small changes?
15	A6 score	The answer code of: Does the person have obsessive interests?
16	A7 score	The answer code of: Is the person over or under-sensitive to smells, tastes, or touch?
17	A8 score	The answer code of: Does the person struggle to socialize with other children?
18	A9 score	The answer code of: Does the person avoid physical contact?
19	A10 score	The answer code of: Does the person show little awareness of dangerous situations?

SAMPLE DATASET

A	B	C	D	E	F	G	H	I	J	K	L	M	N
A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A8_Score	A9_Score	A10_Sc	age	gender	ethnicity	jundice
1	1	1	1	0	0	1	1	0	0	26	f	White-Eur	no
1	1	0	1	0	0	0	1	0	1	24	m	Latino	no
1	1	0	1	1	0	1	1	1	1	27	m	Latino	yes
1	1	0	1	0	0	1	1	0	1	35	f	White-Eur	no

Proposed Approach

PREPROCESSING

- **Missing Values:** Imputed using mean for Age and most frequent values for Ethnicity & Relation via SimpleImputer.
- **Duplicates Removed:** Detected and dropped to prevent redundancy and data leakage.
- **Age Transformation:** Converted Age from years to months for finer resolution.
- **Dataset Balancing:** Split into ASD and non-ASD groups, then balanced via fair sampling.
- **Data Shuffling:** Performed two shuffles to eliminate bias and ensure randomized learning.
- **Feature Scaling:** Applied Min-Max Scaling (0–1 range), especially for Age.
- **Categorical Encoding:** Used One-Hot Encoding to convert categorical variables to numeric.

Proposed Approach

FEATURE SELECTION-RANDOM FOREST

Feature	Importance Score
A4_Score	0.137900
A9_Score	0.096010
A8_Score	0.078809
A1_Score	0.070973
A10_Score	0.070767
A3_Score	0.064245
A5_Score	0.062807
A6_Score	0.053869
Age_Mons	0.044654
A7_Score	0.040172
A2_Score	0.031451
country_of_res_'United States'	0.015779
country_of_res_'United Kingdom'	0.013330
ethnicity_White-European	0.013043
jundice_yes	0.012303

Feature	Importance Score
A5_Score	0.148695
A9_Score	0.148465
A10_Score	0.075429
A4_Score	0.072030
A6_Score	0.071756
A3_Score	0.063911
A2_Score	0.053446
A1_Score	0.044105
A7_Score	0.041864
Age_Mons	0.041611
A8_Score	0.032516
country_of_res_'United States'	0.012704
ethnicity_Asian	0.012210
ethnicity_White-European	0.012162
country_of_res_India	0.010348

Feature	Importance Score
A9_Score	0.115546
A6_Score	0.108041
A4_Score	0.100210
A5_Score	0.099139
A3_Score	0.064374
A10_Score	0.056879
Age_Mons	0.053602
A7_Score	0.050308
A8_Score	0.042794
A1_Score	0.041582
A2_Score	0.035352
ountry_of_res_'United States'	0.015619
ethnicity_White-European	0.014225
relation_Parent	0.011214
relation_Self	0.010257

Proposed Approach

Model	Definition
Decision Tree	A tree-based model that splits data into branches based on feature values, making decisions at each node for classification or regression.
K-Nearest Neighbors (KNN)	A non-parametric model that classifies data points based on the majority class of their nearest K neighbors in the feature space.
Logistic Regression	A statistical model that uses a logistic function to estimate probabilities, commonly used for binary classification problems.
Support Vector Machine (SVM)	A supervised learning model that finds the optimal hyperplane to separate different classes in a high-dimensional space.
Random Forest	An ensemble learning method that builds multiple decision trees and combines their outputs to improve accuracy and reduce overfitting.
XGBoost (Extreme Gradient Boosting)	A powerful gradient boosting algorithm optimized for speed and performance, widely used in competitive machine learning tasks.

Performance Metric	Formula
Accuracy (%)	$\frac{TP+TN}{TP+TN+FP+FN} \times 100$
Precision (%)	$\frac{TP}{TP+FP} \times 100$
Recall (%)	$\frac{TP}{TP+FN} \times 100$
Specificity (%)	$\frac{TN}{TN+FP} \times 100$
F1 Score (%)	$2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \times 100$
AUC Score (%)	Computed from the ROC Curve
ROC (Receiver Operating Characteristic) Curve	$\text{TPR} = \frac{TP}{TP+FN}, \quad \text{FPR} = \frac{FP}{FP+TN}$
Kappa Score	$\frac{p_o - p_e}{1-p_e}$
Log Loss	$-\frac{1}{N}\sum(y\log(\hat{y}) + (1-y)\log(1-\hat{y}))$

Proposed Approach

ML MODEL EVALUATION METRIC FOR CHILD

	Model	Accuracy (%)	Precision (%)	Recall (%)	\
0	Decision Tree	93.10	86.96	95.24	
1	KNN	96.55	91.30	100.00	
2	Logistic Regression	100.00	100.00	100.00	
3	SVM	100.00	100.00	100.00	
4	Random Forest	94.83	87.50	100.00	
5	XGBoost	94.83	87.50	100.00	

	Specificity (%)	F1 Score (%)	AUC Score (%)	Kappa Score (%)	Log Loss
0	91.89	90.91	93.56	85.37	2.4858
1	94.59	95.45	97.30	92.69	1.2429
2	100.00	100.00	100.00	100.00	0.0000
3	100.00	100.00	100.00	100.00	0.0000
4	91.89	93.33	95.95	89.14	1.8643
5	91.89	93.33	95.95	89.14	1.8643

ML MODEL EVALUATION METRIC FOR ADULT

Model	Accuracy (%)	Precision (%)	Recall (%)	\
Decision Tree	93.42	92.86	95.12	
KNN	93.42	90.91	97.56	
Logistic Regression	100.00	100.00	100.00	
SVM	100.00	100.00	100.00	
Random Forest	96.05	95.24	97.56	
XGBoost	93.42	92.86	95.12	

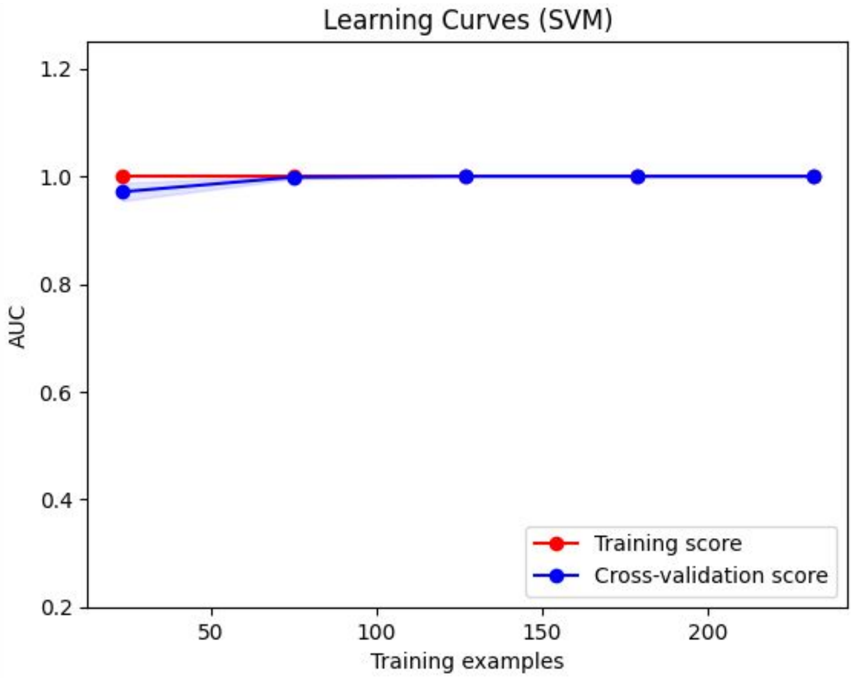
Specificity (%)	F1 Score (%)	AUC Score (%)	Kappa Score (%)	Log Loss
91.43	93.98	93.28	86.73	2.3713
88.57	94.12	93.07	86.68	2.3713
100.00	100.00	100.00	100.00	0.0000
100.00	100.00	100.00	100.00	0.0000
94.29	96.39	95.92	92.04	1.4228
91.43	93.98	93.28	86.73	2.3713

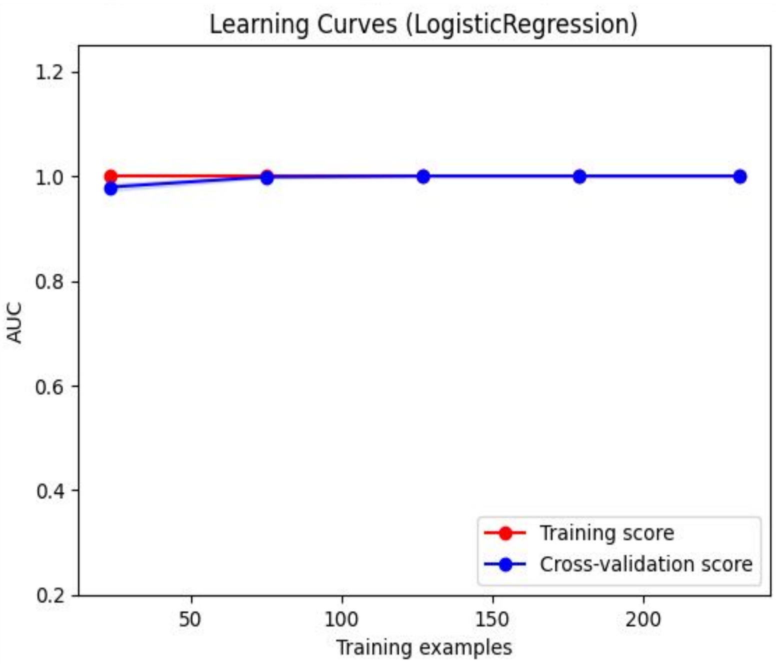
Proposed Approach

ML MODEL EVALUATION METRIC FOR COMBINED

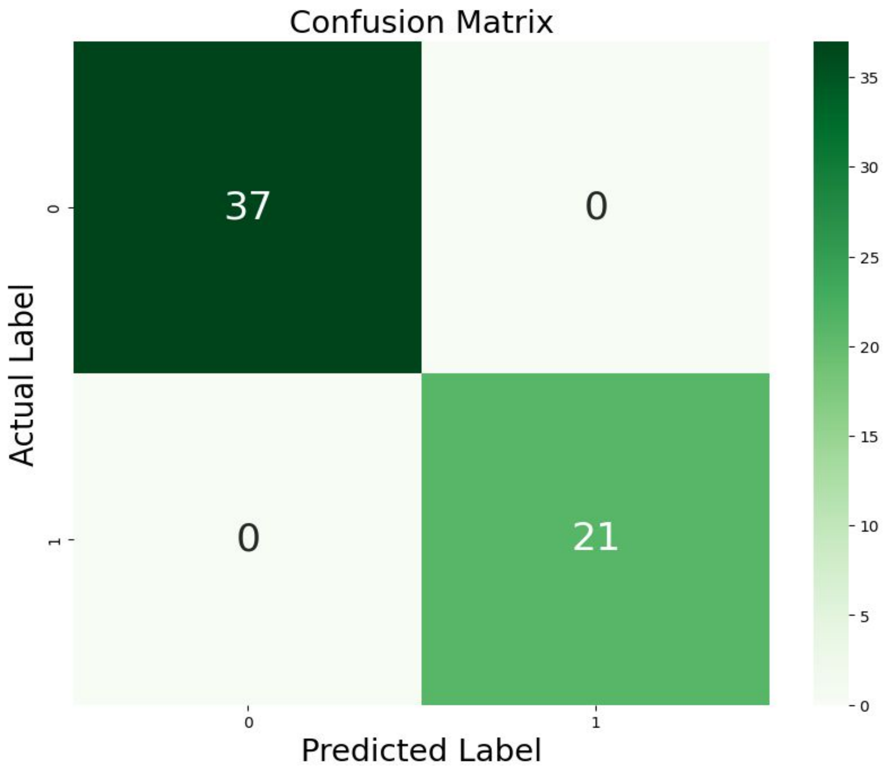
Model	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1 Score (%)	AUC Score (%)	Kappa Score (%)	Log Loss
Decision Tree	92.46	88.71	87.30	94.85	88.00	91.08	82.51	2.7169
KNN	94.97	88.41	96.83	94.12	92.42	95.47	88.68	1.8112
Logistic Regression	100.00	100.00	100.00	100.00	100.00	100.00	100.00	0.0000
SVM	100.00	100.00	100.00	100.00	100.00	100.00	100.00	0.0000
Random Forest	97.49	98.33	93.65	99.26	95.93	96.46	94.12	0.9056
XGBoost	98.49	98.39	96.83	99.26	97.60	98.05	96.50	0.5434

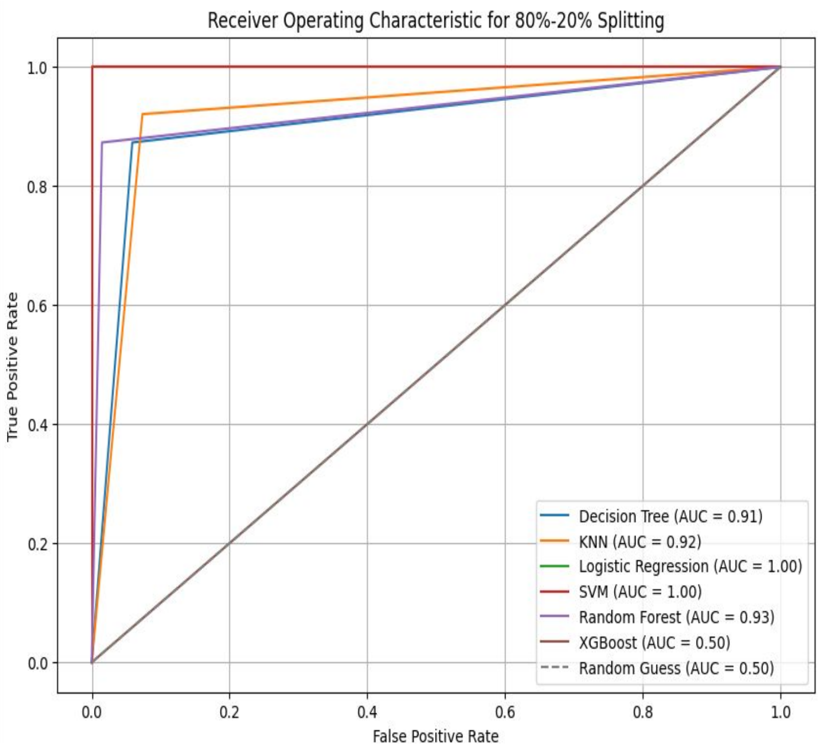
Proposed Approach





Proposed Approach





Proposed Approach

Clustering Algorithms

Clustering Method	Definition
K-Means	Partitions data into k clusters by iteratively minimizing intra-cluster variance.
Agglomerative	A hierarchical method that merges data points into clusters based on similarity.
GMM (Gaussian Mixture Model)	Uses Gaussian distributions to model clusters probabilistically.
Spectral Clustering	Transforms data into a graph and applies clustering in lower dimensions.
Birch	Efficiently clusters large datasets using a tree-based hierarchical approach.

Proposed Approach

Performance metrics

Performance Metric	Definition
NMI (Normalized Mutual Information)	Measures the mutual dependence between true and predicted clusters. It is normalized between 0 and 1, where 1 indicates perfect clustering.
ARI (Adjusted Rand Index)	Evaluates the similarity between true and predicted clusters by considering all pairs of points and their clustering agreements, adjusted for chance. It ranges from -1 to 1, where 1 represents perfect clustering.
SC (Silhouette Coefficient)	Measures how well each point is clustered by considering intra-cluster cohesion and inter-cluster separation. It ranges from -1 to 1, where a higher value indicates better-defined clusters.

Tool	Purpose	Why It's Useful
t-SNE	Visualizes clusters	See how data points group and separate in low dimensions
Contingency Matrix	Evaluates cluster-la bel match	Measures agreement with true classes (if known)

Proposed Approach

Clustering Model Evaluation Metrics for Child

Model	NMI (%)	ARI (%)	Silhouette Score (%)
KMeans	61.60	68.48	18.29
Gaussian	15.61	15.62	15.65
Agglomerative	28.75	24.09	17.47
Spectral	35.76	27.61	19.31
Birch	27.69	28.51	16.89

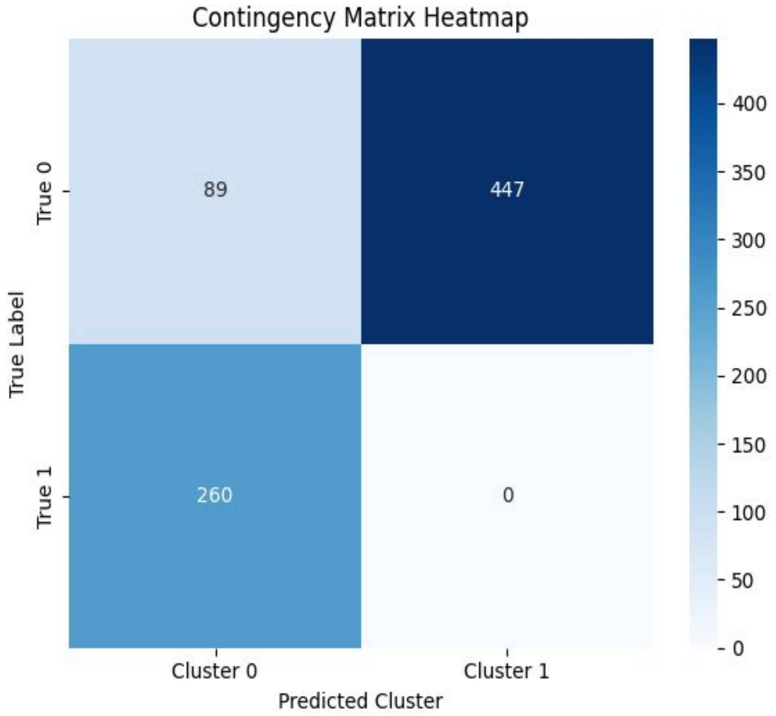
Clustering Model Evaluation Metrics for Adult

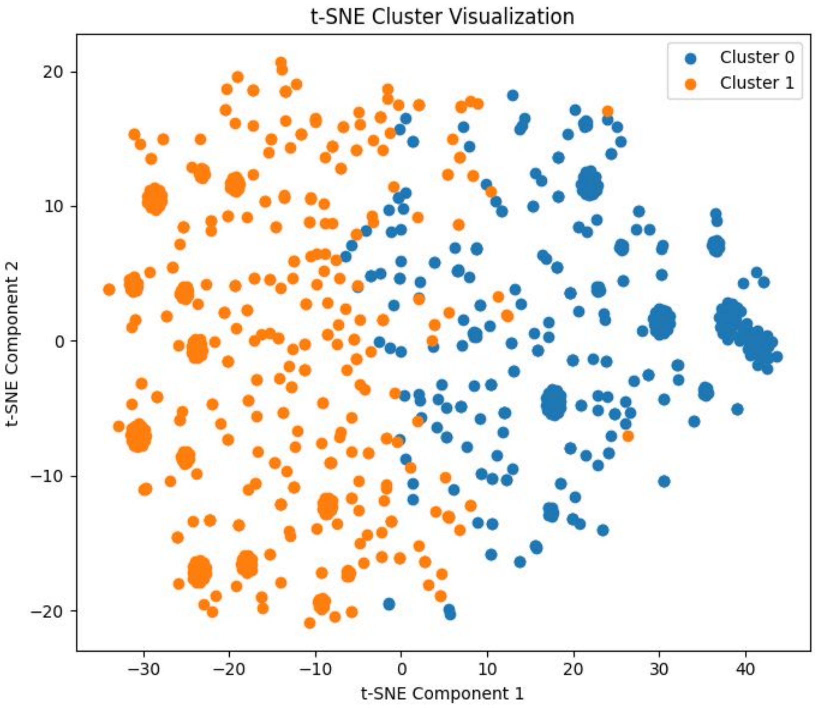
Model	NMI (%)	ARI (%)	Silhouette Score (%)
KMeans	74.08	78.68	23.04
Gaussian	35.46	38.55	19.83
Agglomerative	47.98	49.11	19.80
Spectral	74.08	78.68	23.01
Birch	54.85	56.86	20.98

Model	NMI (%)	ARI (%)	Silhouette Score (%)
KMeans	59.24	61.72	20.71
Gaussian	32.08	29.91	17.92
Agglomerative	48.13	56.98	18.45
Spectral	59.81	62.51	20.68
Birch	53.22	64.74	17.77

Clustering Model Evaluation Metrics for Combined

Proposed Approach





Proposed Approach

DL Algorithm

Model	Definition	Layers Used	ReLU Function
Dense Model (Baseline)	Two fully connected layers with ReLU activation.	64 and 32 neurons, Sigmoid output layer.	Used for non-linearity.
Dropout Model	Uses dropout layers to reduce overfitting.	Dropout layers between dense layers.	Works with ReLU to improve generalization.
Batch Normalization Model	Normalizes inputs for stable training.	Batch normalization after dense layers.	Helps accelerate training and convergence.
LSTM Model	Captures temporal dependencies in data.	LSTM layers, dropout layers.	Rarely used; tanh and sigmoid preferred.
Residual Model	Uses residual blocks to aid deep network training.	Shortcut connections, residual blocks, Sigmoid output.	Applied in residual blocks.
Sigmoid Model	Variation of Dense model with batch normalization and dropout.	Batch normalization, ReLU activation, Sigmoid output.	Used before the sigmoid output activation.

Performance Metrics

Performance Metric	Formula
Accuracy (%)	$\frac{TP+TN}{TP+TN+FP+FN} \times 100$
Precision (%)	$\frac{TP}{TP+FP} \times 100$
Recall (%)	$\frac{TP}{TP+FN} \times 100$
Specificity (%)	$\frac{TN}{TN+FP} \times 100$
F1 Score (%)	$2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \times 100$
AUC Score (%)	Computed from the ROC Curve
ROC (Receiver Operating Characteristic) Curve	$\text{TPR} = \frac{TP}{TP+FN}, \quad \text{FPR} = \frac{FP}{FP+TN}$
Kappa Score	$\frac{p_o - p_e}{1-p_e}$
Log Loss	$-\frac{1}{N}\sum(y\log(\hat{y}) + (1-y)\log(1-\hat{y}))$

Proposed Approach

DL Model Evaluation Metrics for Child

Model Evaluation Metrics:

	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC AUC (%) \
Batch Norm	93.442623	90.909091	96.774194	93.75	99.462366
Dropout	96.721311	93.75	100.0	96.774194	100.0
Dense	96.610169	93.333333	100.0	96.551724	100.0
LSTM	96.721311	93.75	100.0	96.774194	99.139785
Residual	91.525424	84.848485	100.0	91.803279	98.847926
Sigmoid	96.610169	93.333333	100.0	96.551724	100.0

	Log Loss	Confusion Matrix
Batch Norm	0.121772	[[27, 3], [1, 30]]
Dropout	0.068395	[[29, 2], [0, 30]]
Dense	0.079179	[[29, 2], [0, 28]]
LSTM	0.119988	[[29, 2], [0, 30]]
Residual	0.278434	[[26, 5], [0, 28]]
Sigmoid	0.068138	[[29, 2], [0, 28]]

DL Model Evaluation Metrics for Adult

	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC AUC (%) \
Batch Norm	90.731707	88.181818	94.174757	91.079812	97.192081
Dropout	90.243902	91.0	89.215686	90.09901	97.48715
Dense	98.571429	97.297297	97.297297	97.297297	99.97376
LSTM	89.268293	89.215686	89.215686	89.215686	97.039787
Residual	94.285714	83.72093	97.297297	90.0	98.976647
Sigmoid	94.285714	87.179487	91.891892	89.473684	99.002886

	Log Loss	Confusion Matrix
Batch Norm	0.25387	[[89, 13], [6, 97]]
Dropout	0.240706	[[94, 9], [11, 91]]
Dense	0.050992	[[102, 1], [1, 36]]
LSTM	0.235943	[[92, 11], [11, 91]]
Residual	0.154089	[[96, 7], [1, 36]]
Sigmoid	0.12591	[[98, 5], [3, 34]]

Proposed Approach

DL Model Evaluation for Combined

Model Evaluation Metrics:

	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC AUC (%)
Batch Norm	90.943396	89.781022	92.481203	91.111111	97.223172
Dropout	93.962264	94.615385	93.181818	93.89313	98.373775
Dense	94.949495	87.671233	98.461538	92.753623	98.924234
LSTM	93.207547	91.911765	94.69697	93.283582	97.826954
Residual	85.353535	69.148936	100.0	81.761006	97.744361
Sigmoid	94.444444	85.526316	100.0	92.198582	98.554078

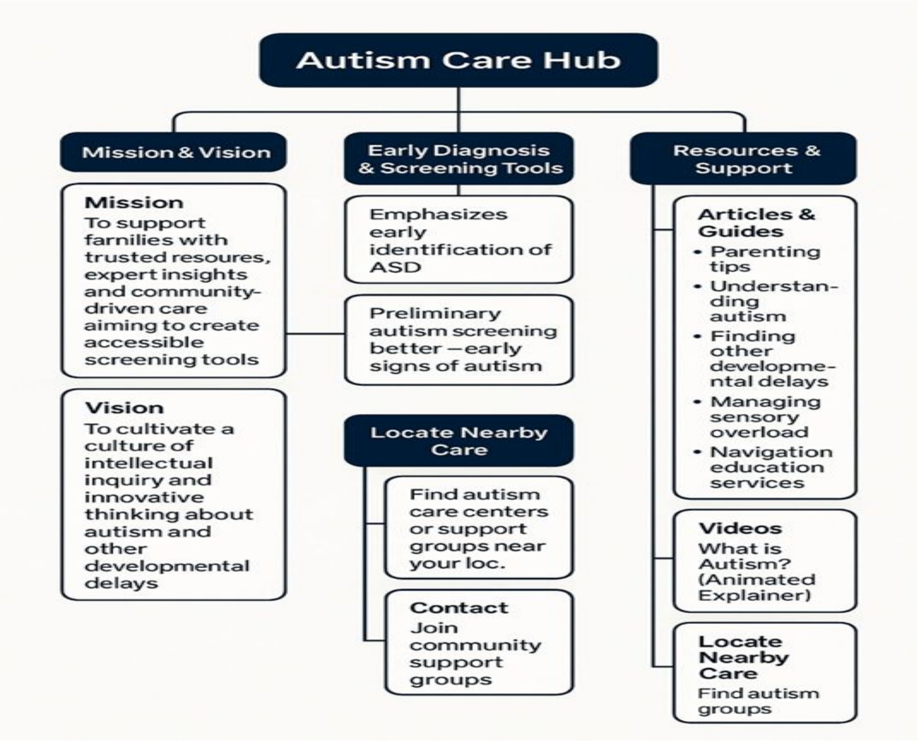
	Log Loss	Confusion Matrix
Batch Norm	0.249044	[[118, 14], [10, 123]]
Dropout	0.169654	[[126, 7], [9, 123]]
Dense	0.168747	[[124, 9], [1, 64]]
LSTM	0.184441	[[122, 11], [7, 125]]
Residual	0.424015	[[104, 29], [0, 65]]
Sigmoid	0.190117	[[122, 11], [0, 65]]

Proposed Approach

Learning Curve for Dropout Model

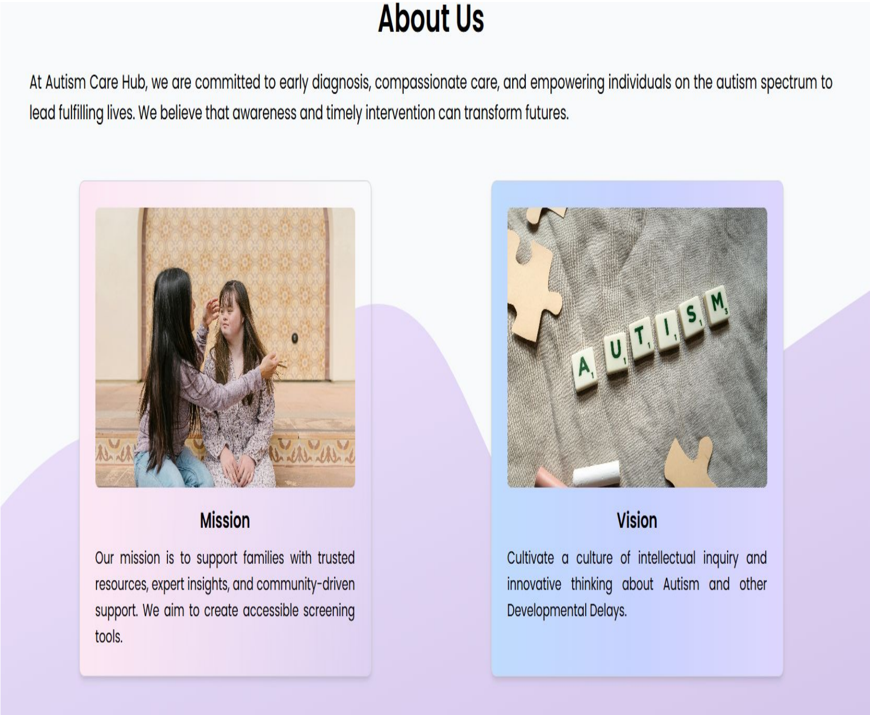
Proposed Approach

AUTISM CARE HUB

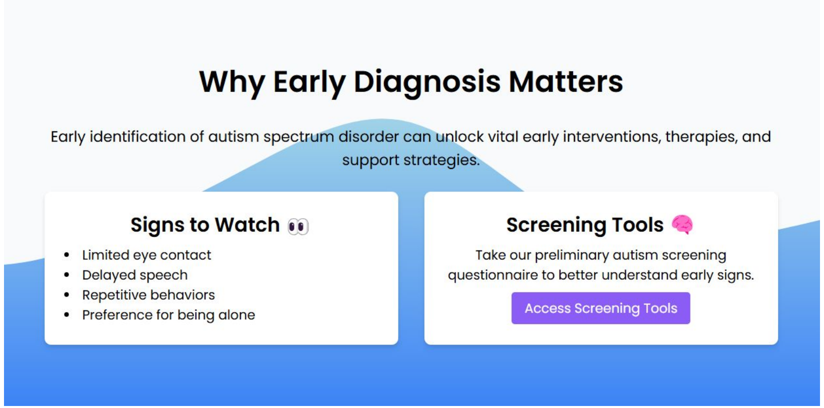


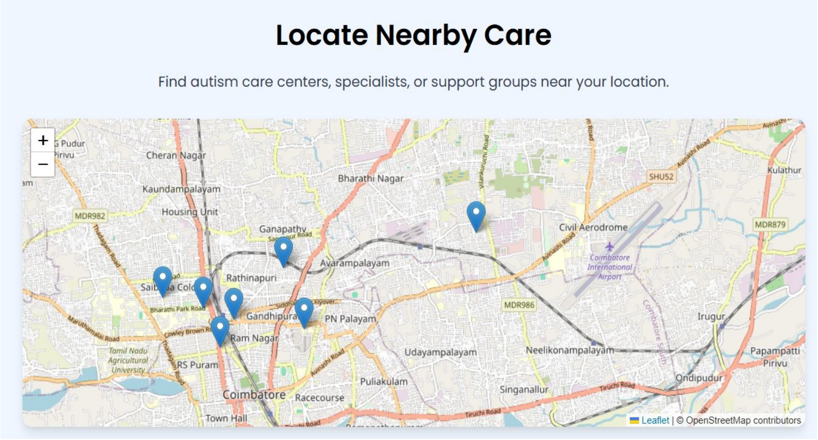
Proposed Approach

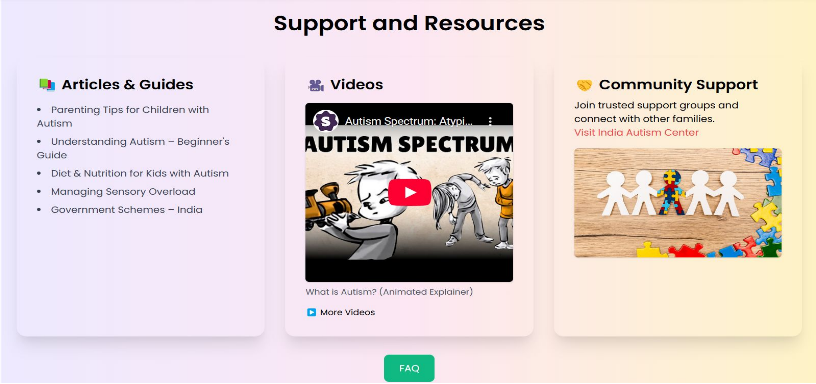
Autism Care Hub -Website Overview



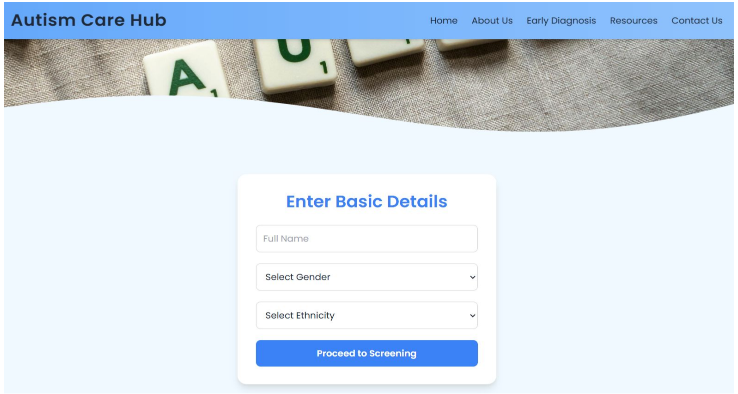
Proposed Approach

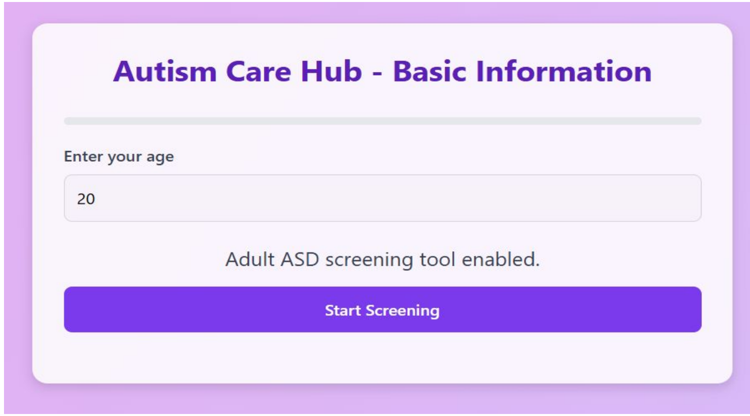


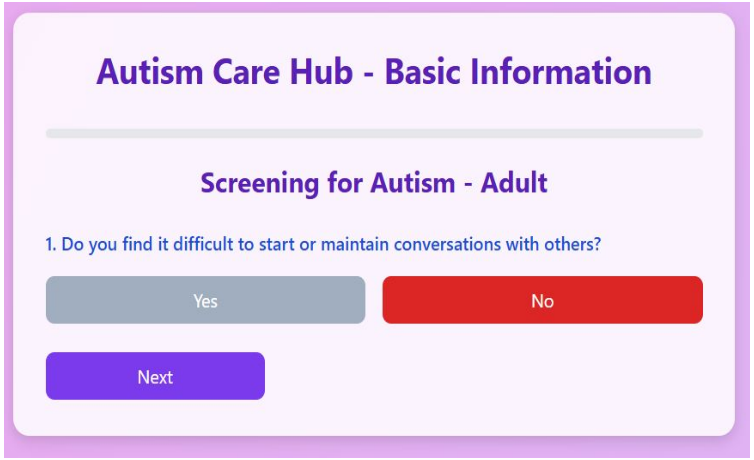


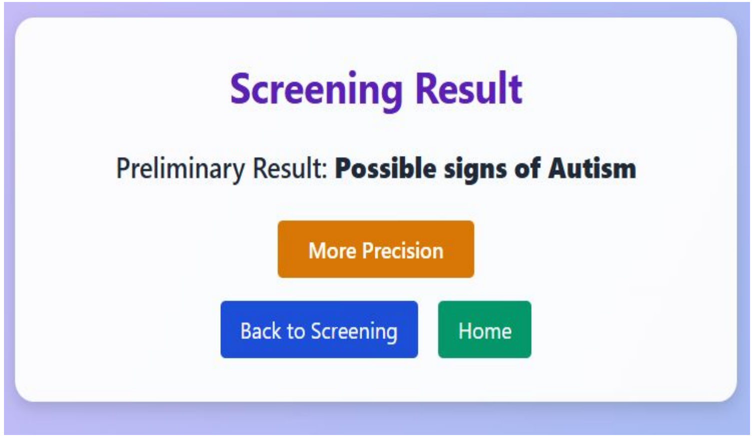


Proposed Approach

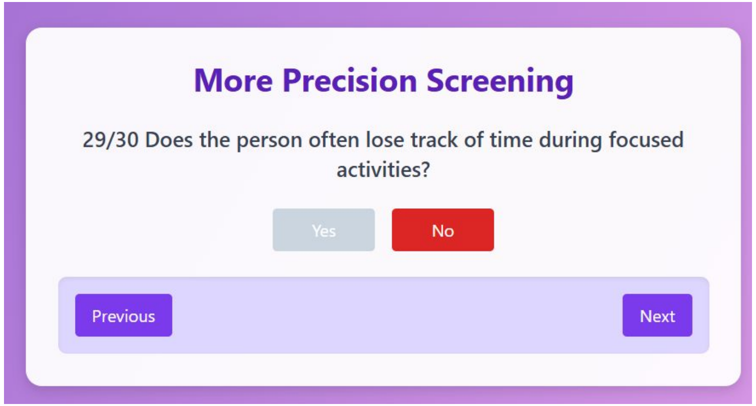


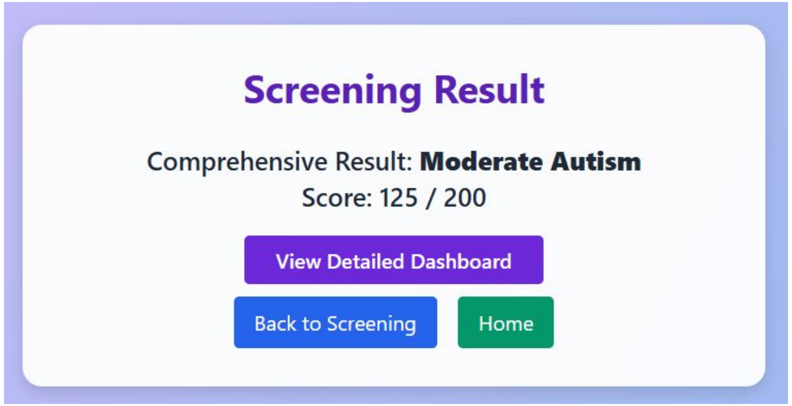


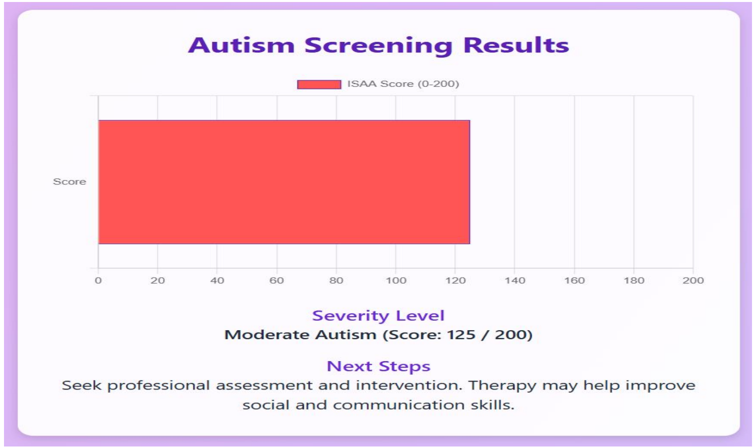




Proposed Approach







Website link:
https://autism-care-hub.netlify.app/

Results and Discussion for ML

🔹 **SVM & Logistic Regression**

- 100% Accuracy, Precision, Recall, F1, AUC, Specificity, Kappa (all datasets)
- Zero Log Loss → perfect confidence
- Best generalization; supports prior research

🔹 **Random Forest & XGBoost**

- ~94.8% Accuracy on Child dataset
- Improved to 97.4% (RF) and 98.4% (XGB) on Combined data
- Performs better with diverse training sets

🔹 **K-Nearest Neighbors (KNN)**

- Accuracy improved in Combined dataset (94.97%)
- High Log Loss (>1.2) on Child & Adult → uncertain predictions

Results and Discussion for ML

🔹 **Decision Tree**

- ~92–93% Accuracy across datasets
- Highest Log Loss, lowest Kappa → less reliable
- Not ideal for complex autism data

🔍 **Overall Insights**

- Combined dataset boosts model performance
- SVM & Logistic Regression = top models for consistent, confident autism prediction

Results and Discussion for Clustering

➔ **KMeans**

- Best overall performer (NMI: 74.08%, ARI: 78.68% on Adult).
- Strong clustering across datasets, ideal for structured label alignment.

➔ **Spectral Clustering**

- Matches KMeans on Adult data, good on Combined (NMI: 59.81%).
- Great for non-linear boundaries.

➔ **Agglomerative Clustering**

- Moderate results, best on Combined (NMI: 48.13%).
- Suitable for hierarchical patterns.

Results and Discussion for Clustering

➔ **Gaussian Mixture (GMM)**

- Weak performance, especially on Child data (NMI: 15.61%).
- Not suitable for this task.

➔ **Birch**

- Mid-range performance (Adult NMI: ~54%).
- Scalable but less accurate.

🔍 **Overall Insights**

- Adult dataset consistently leads to better clustering results, possibly due to clearer feature separation in adult autism profiles.
- Combined dataset balances child and adult characteristics, giving slightly lower but stable scores — beneficial for generalized models.
- KMeans and Spectral are the most effective algorithms overall for this use case.

Results and Discussion for DL

1. Dense Network

- Top performer across all datasets.
- Child: Perfect scores (100% Precision, Recall, F1, AUC).
- Combined: Highest Accuracy (94.05%) and AUC (98.94%).
- Inference: Most robust and reliable model.

2. Dropout Model

- Consistently high performance with minimal overfitting.
- F1 Score ~96–99% across datasets.
- Inference: Excellent balance of accuracy and generalization.

3. LSTM

- High scores on Child and Combined datasets.
- Slightly behind Dense/Dropout on Adult data.
- Inference: Ideal for sequential data or temporal features.

Results and Discussion for DL

4. Batch Normalization Model

- Consistent metrics across all datasets.
- Accuracy ~90–93%, strong AUC values.
- Inference: Stable and noise-resistant training.

5. Sigmoid Model

- Perfect Recall in Child dataset, but low Precision elsewhere.
- High sensitivity, but risk of false positives.
- Inference: Best for recall-focused tasks.

6. Residual Model

- Lowest performance; Combined Accuracy: 85.35%.
- Highest Log Loss; weaker overall scores.

Results and Discussion for DL

Choosing Backend?

Model	Deploy?	Why
Logistic Regression	✅ Best	Accurate, fast, confident, interpretable
SVM	✅ Best	Same as above; more robust margins
Dense Network	✅ Optional	Best DL model, Works best with **GPU** or a **high-performance CPU**
Dropout Model	✅ Optional	Strong DL generalization, stable
KNN, DT, GMM	❌ No	Poor confidence or slow inference

Conclusions

Aspect	Base Paper	Our Proposed Work
DL Model	Not included	5 Custom DL model is used
Feature Selection	Chi-Square	Random Forest
Deployment	Desktop GUI	Fully deployed, web-based diagnostic platform that integrates a two-phase screening process (AQ-10 followed by a 30-item ISAA-based refinement) with a backend SVM model, offering real-time predictions, visual result interpretation, and user-friendly
Best Performing Model	Children: SVM & LR (100%) Adults: LR (97.14%)	Children: SVM & LR (100%) Adults: SVM & LR (100%)
Performance Metrics Use	8 performance metrics	Same metrics + **log loss** and **false negative rate** analysis, especially for DL.

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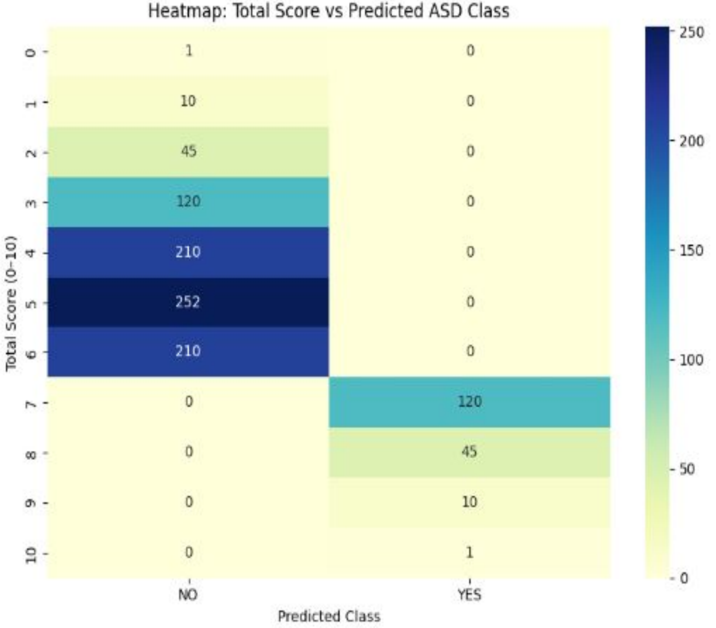
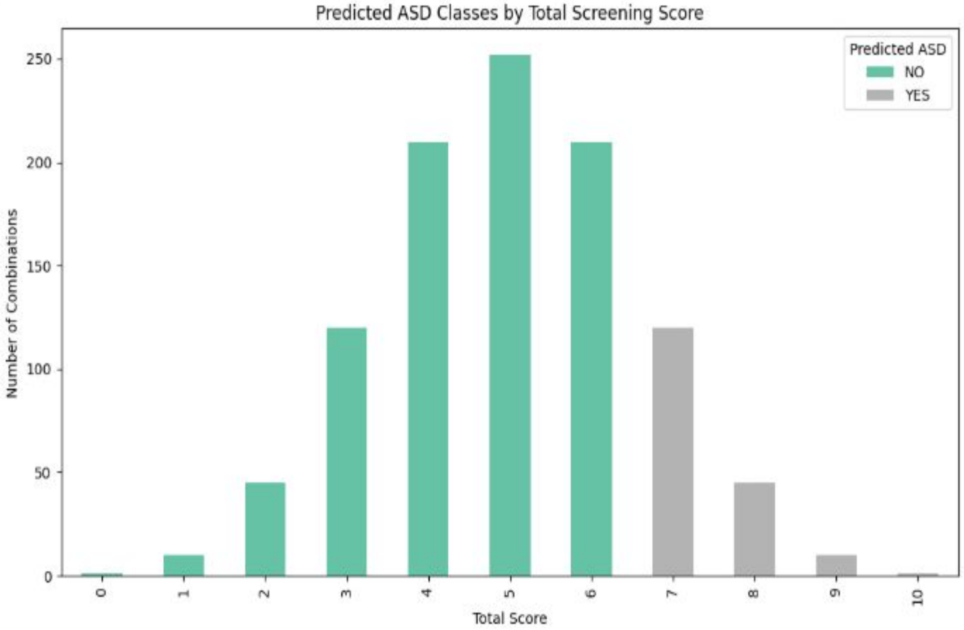
ISN'T SVM AND LR OVERFITTING? NO



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Model accuracy on all 1024 combinations: 100.00%
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