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AUTISM SPECTRUM DISORDER DETECTION USING GRAPH-BASED NEURAL NETWORKS APPROACH

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Abstract

Autism Spectrum Disorder (ASD) is a neuro-developmental condition characterized by challenges in social interaction and communication. Early and accurate diagnosis is crucial but remains challenging due to complex behavioral patterns and imbalanced datasets. Existing models lack robustness in handling data imbalance and often overlook the relational structure between features. This creates a significant research gap in developing a reliable and generalizable model for ASD prediction. The problem addressed in this study is the ineffective classification of ASD cases caused by class imbalance and feature selection. The objective is to design a model that improves diagnostic accuracy while handling these limitations. To achieve this, an ensemble deep learning model combining Graph Attention Network (GAT) and Artificial Neural Network (ANN), called GAT-ANN, is proposed. The methodology involves feature selection using Graph-based Feature Selection (GBFS), class imbalance handling through GAT-based class imbalance handler and GAN-based data augmentation, and classification using the GAT-ANN model. Results show that the model achieved 99.98% and 99.99% accuracy for children and adult datasets. These findings demonstrate good performance of GAT-ANN over traditional models. In conclusion, the GAT-ANN model provides a reliable framework for ASD prediction.

Keywords- Autism Spectrum Disorder, GAT-ANN, Feature Selection, Class Imbalance, GAN, SMOTE, Deep Learning

1 Introduction

Autism Spectrum Disorder (ASD) is a complex neuro-developmental condition characterized by challenges in social interaction, communication, and repetitive or restrictive behaviors. It typically manifests in early childhood and affects individuals across their lifespan, albeit differently [1], [2]. The World Health Organization (WHO) reports that approximately 1 in 100 children globally are affected by ASD, highlighting its significant prevalence and the critical need for early diagnosis and intervention [3]. The impact of ASD varies by age; in children, it often presents as delayed speech, poor eye contact, and difficulties in understanding social cues [4], while in adults it can lead to persistent issues in social relationships, employment, and independent living [5].Diagnosing ASD traditionally relies on clinical evaluations and behavioral assessments conducted by specialists using standardized tools such as the Autism Diagnostic Observation Schedule (ADOS) [6] and Autism Diagnostic Interview-Revised (ADI-R) [7]. Although reliable, these manual diagnostic approaches are time-consuming, costly, and require trained professionals, which can lead to delays in diagnosis and treatment, especially in low-resource settings. To address this challenge, several early screening tools like the Modified Checklist for Autism in Toddlers (M-CHAT) [8] and Quantitative Checklist for Autism in Toddlers (Q-CHAT) [9] have been developed. These tools enable faster preliminary screening but still require expert interpretation and may lack sufficient precision in complex cases.

With the advancement of Artificial Intelligence (AI), particularly in the domain of Machine Learning (ML), researchers have increasingly explored automated prediction of ASD using

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screening data [10]-[20]. These approaches leverage supervised learning algorithms to detect patterns in questionnaire responses and identify individuals at risk of ASD. However, despite these advances, existing ML-based methods face several challenges. Notably, they often overlook feature selection [10], [20], the process of identifying the most relevant data attributes—and struggle to effectively handle class imbalance [10]-[14], [16], [17], [19], [20], a common issue in ASD datasets where non-ASD samples significantly outnumber ASD cases. Moreover, very limited research has explored Deep Learning (DL)-based approaches for ASD prediction [13], which have the potential to capture more complex patterns than traditional ML models. Moreover, the current models fail to integrate effective feature selection strategies and class imbalance handling, which are crucial for improving prediction accuracy and model robustness. To address these limitations, this study presents a novel methodology that introduces Graph-Based Feature Selection (GBFS) to identify the most informative features, followed by an ensemble model called GAT-ANN. In this model, the Graph Attention Network (GAT) is employed to manage class imbalance and refine feature representations, while Artificial Neural Network (ANN) serves as the final classifier for predicting ASD with improved performance and interpretability. The contributions of the work are as follows

- This work introduced a GBFS method to enhance the quality of input features by capturing inter-feature relationships.
- This work proposed a novel GAT-ANN model that combines GAT for handling class imbalance and ANN for final prediction.
- This work applied Conditional Generative Adversarial Network (C-GAN) augmentation to increase data diversity while maintaining distribution fidelity.
- This work evaluated the model on both children and adult ASD datasets, showing superior accuracy and robustness compared to traditional ML methods.

The manuscript is organized in the following way. Section II discusses existing ML and DL-based ASD prediction approaches. Section III presents the methodology used in this work. Section IV discusses results of GAT-ANN and Section V presents conclusion of the work.

2 Literature Survey

This section presents the existing ML and DL-based ASD prediction approaches presented in recent years. This section also discusses the current gap, which has not been addressed in the existing approaches. D. D. Khudhur et al. [10], aimed at developing an accurate classification approach for early ASD detection across different age groups, mainly adults, adolescents, children and toddlers. For ASD detection used various ML approaches, which included Random Forest (RF), Logistic Regression (LR), Naïve Bayes (NB), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Decision Tree (DT). For evaluating different ML models, considered UCI and Kaggle dataset, i.e., adults (704 samples), adolescents (104 samples), children (292 samples) and toddlers (1054 samples). All the datasets had 21 features, except toddlers, which had only 19 features. Findings showed that RF, LR, DT showed better performance achieving 100% accuracy. This work did not consider handing class imbalance and used less samples for predicting ASD in different age groups. Also, this work failed to consider feature selection. M. S. Farooq et al. [11], aimed at enhancing early detection of ASD in adults and children using federated-learning (FL). In their work, FL was used for training SVM and LR locally and their outputs were then aggregated on central server, where meta-classifier determined best detection approach. In this work, a feature selection approach was added which provided better results. For this study, four ASD datasets were considered, two datasets from UCI, where children ASD dataset had 692 samples with 21 attributes and adult ASD dataset had 704 samples with 21 attributes and two datasets from Kaggle, which had same values as UCI data, but was preprocessed having 654 samples in children ASD dataset with 19 attributes and 700 samples in adult dataset with 19 attributes. The proposed FL approach achieved 98% accuracy for children and 81% accuracy for adults. This work did not consider handing class imbalance.

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M. Mohi et al. [12], aim was to evaluate effectiveness of ML in predicting ASD using health and behavior-related attributes. Hence, in this work, Gaussian NB (GNB), Bernoulli NB (BNB), Multinomial NB (MNB), Quadratic Discriminant Analysis (QDA), SVM, RF, and LR were used for prediction. In this work considered preprocessing and feature optimization for providing better prediction outcomes. For this study, the children and adult UCI dataset were considered, which had 292 and 704 samples respectively with 21 attributes. Among all ML models, RF achieved better results, achieving 100% accuracy on both adult and children's datasets. This work failed to handle class imbalance. M. K. Al-Muhanna et al. [13], developed a lightweight and automatic AI-based approach for accurate and efficient ASD detection, hence, presented a DL approach called Auto-Encoder-Warm Equilibrium Learner (AE_2L). In AE_2L, feature dimensionality reduction using warm-optimized selection and hyper parameter-tuning using equilibrium optimization was used for enhancing prediction performance. For evaluation, considered the children and adult ASD dataset from UCI. Findings showed that AE_2L achieved better results in terms of accuracy. This work has not addressed problem of class imbalance. R. A. Result et al. [14], aimed at enhancing ASD detection using clustering and ML approaches. Hence, used ML approaches, which included NB, KNN, LR, SVM, DT, RF, eXtreme Gradient Boosting (XGB), ANN, K-means, Gaussian Mixture Model (GMM), Agglomerative, Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH) and Spectral Clustering with 5 k-folds. They used Chi-Square for feature selection. For this study, the UCI adult and children ASD dataset were used, where findings showed that LR and SVM achieved 100% accuracy on children dataset and LR achieved 97.14% accuracy on adults ASD dataset. This work failed to handle class imbalance issues.

S. S. Rajagopalan et al. [15], developed and validated ML for ASD detection using minimal twenty-four background and medical features. In this work, they used for ML approaches, LR, DT, RF, and XGB. For selecting features, the Explainable AI (XAI) was used. For this study, they collected data from 30,660 individual, where 15330 were ASD samples and 15330 were non-ASD samples. Findings showed that LR, DT, RF and XGB achieved 75.2%, 73.2%, 81.2% and 81.7% accuracy respectively. The samples in their dataset were equal; hence, there was no need for handling class imbalance. S. A. Alzakari et al. [16], developed ML approach for ASD detection and recommended personalized education approach on basis of individual traits. In this work, a two-phase approach was utilized. In first phase, SVM and LR were used for predicting ASD, i.e., ensemble approach, where Chi-Square, Bi-directional Elimination and Principal-Component Analysis (PCA) were utilized as feature selector. The second phase focused on identifying suitable teaching strategy on basis of verbal and behavioral responses. For this study, the Kaggle toddler ASD dataset and UCI children ASD dataset were combined together, creating more samples for prediction. Findings showed that the LR and SVM ensemble approach achieved 94% accuracy. They failed to handle class imbalance issue in ASD merged dataset. S. W. Kadhum et al. [17], developed ML approach for ASD prediction in children using behavioral features. In this work, first, data pre-processing was applied, followed by feature selection using Pearson Coefficient Correlation (PCC) and ML approaches, mainly NB, KNN, DT, SVM and AdaBoost (AB) were used for ASD prediction. For this study, they used a Kaggle children ASD dataset having 1250 samples, where achieved 99.2% accuracy using NB and 97.2% accuracy using KNN. This work failed to handle class imbalance.

N. Mumenin et al. [18], aimed at developing ML approach for ASD prediction across various age groups. Hence, in this work, an ensemble approach was presented which combined CatBoost (CB), Extra-Tree (ETs) and RF. For classifier this work used ANN. Further, for feature selection, used Safe-Level Synthetic Minority Oversampling Technique (SL-SMOTE). For understanding feature importance, used SHapley Additive exPlanations (SHAP) along with Monte-Carlo dropout assessed prediction uncertainty. For this study, the UCI and Kaggle datasets were used, i.e., adults, adolescents, children and toddlers. Findings showed that the approach achieved an average of 99.89% accuracy on different datasets after applying SL-SMOTE. This work has handled class-imbalance using SL-SMOTE.N. Haque et al. [19], evaluated ML approaches for ASD detection in

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children and toddlers, hence, used LR, SVM, KNN, DT and RF. For this work, they used toddler ASD dataset from Kaggle and children ASD dataset from UCI. Also, this work collected real-world dataset, where the age of the children ranged from 4 to 11. Findings showed that LR, SVM, DT and RF achieved 100% accuracy, but failed to consider feature selection and handle class imbalance problem. D. M. Setu et al. [20], evaluated and compared different ML approaches for ASD detection. This study analyzed 22 studies, in which 18 studies used ML models and 4 studies employed DL models. This analysis was conducted to analyze how the ML and DL performance varies for predicting ASD. The study also reviewed range of behavioral, clinical and neuro-imaging datasets from children across various age groups for understanding how ASD can be predicted. From the findings, it was seen that the LR, RF and XGB in most of the studies have achieved 100% accuracy, but have failed to handle class imbalance. Further, the DL approaches, like Convolutional Neural Network (CNN), achieved 99.39% accuracy, mainly for neuro-imaging data. The complete summary of the literature survey is given in Table 1.

Table 1. Literature Survey Summary

Ref.	Model Type	Preprocessing	Feature Selection	Class Imbalance
[10]	ML	No	No	No
[11]	ML	Yes	Yes	No
[12]	ML	Yes	Yes	No
[13]	DL	Yes	Yes	No
[14]	ML	Yes	Yes	No
[15]	ML	Yes	Yes	Yes
[16]	ML	Yes	Yes	No
[17]	ML	Yes	Yes	No
[18]	ML	Yes	Yes	Yes
[19]	ML	Yes	No	No

From the literature review on ASD prediction, shows that most existing works either do not employ feature selection or rely on conventional methods without fully capturing the relationships between features. For example, [10], [12], and [16] does not address feature selection effectively, while others such as [14] and [15] use traditional methods like Chi-Square or XAI. Furthermore, a significant limitation across most studies is the lack of class imbalance handling, as observed in [10]-[14], [16],[17], [19] and [20], which compromises prediction performance, particularly in datasets with minority ASD samples. Although some studies such as [18] apply techniques like SL-SMOTE, these are not deeply integrated into DL framework. To overcome these limitations, this study introduces a GBFS method and proposes a novel deep ensemble model, GAT-ANN, combining GAT and ANN to enhance ASD prediction accuracy and robustness. The methodology is discussed in detail in next section.

3 Methodology

This section outlines the proposed architecture, detailing the datasets used, preprocessing steps, data augmentation using C-GAN, application of SMOTE, GBFS method, the GAT-ANN model for classification, and finally, the performance evaluation metrics employed to assess the effectiveness of the GAT-ANN approach.

3.1 Architecture

The overall architecture of this study is presented in Figure 1. Initially, the UCI children and adult ASD datasets were obtained from sources [20] and [21], with detailed information provided in Section 3.2. These datasets underwent a preprocessing stage, as explained in Section 3.3. Following preprocessing, the framework proceeded through seven distinct phases of prediction. In Phase 1, the

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cleaned data was directly used for prediction using the proposed Graph Attention Network (GAT) integrated with ANN (GAT-ANN), and the model's performance was assessed. Phase 2 involved applying feature selection before prediction with GAT-ANN. In Phase 3, feature selection was followed by class imbalance handling using proposed GAT-ANN, after which prediction was conducted. Phase 4 handled class imbalance using SMOTE and applied feature selection, followed by GAT-ANN prediction. In Phase 5, the data was first augmented using GAN, then class imbalance was handled using SMOTE, and then processed through feature selection before being input into GAT-ANN. Phase 6 incorporated GAN-based augmentation followed by the GAT-ANN class imbalance handler and prediction using GAT-ANN. Finally, Phase 7 involved GAN augmentation, feature selection, class imbalance handling with the GAT-ANN handler, and prediction using GAT-ANN. Further details on GAN augmentation are provided in Section 3.4, SMOTE in Section 3.5, GBFS in Section 3.6, the GAT-ANN class imbalance handler and classifier in Section 3.7, and performance metrics in Section 3.8.

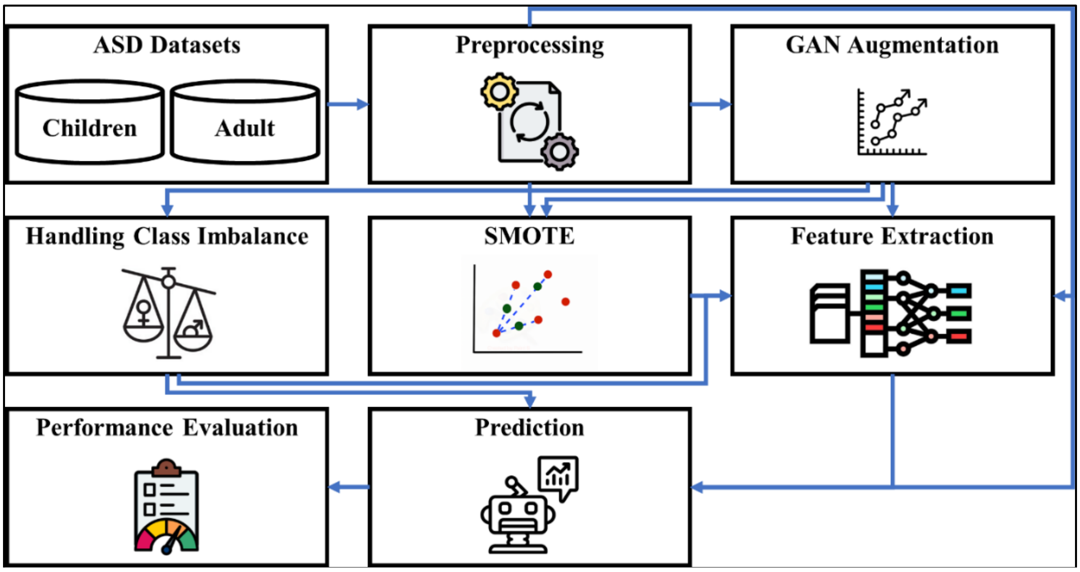

Figure 1. ASD Prediction Architecture.

3.2 Datasets

In this work, two datasets for ASD prediction have been used. The first dataset is children ASD dataset, which has a total of 21 attributes, with total of 292 samples, where 141 are ASD samples and 151 non-ASD samples. The dataset is open-accessible and can be downloaded from [20]. The dataset has missing values in "ethnicity" having count of 43, "age" having count of 4 and "relation" having count of 43. The dataset attributes have categorical, binary and continuous types. Further, in the second dataset, which is adult ASD dataset, similar to children ASD dataset has 21 attributes, where total of ASD samples is 189 and non-ASD samples is 515. The dataset is open-accessible and can be downloaded from [21]. The dataset has missing values in "ethnicity" having count of 95, "age" having count of 2 and "relation" having count of 95. The dataset attributes have categorical, binary and continuous types. The complete summary of the dataset considered for this study is given in Table 2. Further, in the next step the preprocessing of the two datasets was performed, which is discussed in detail in Section 3.3.

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Table 2. Dataset Summary

SL. No	Dataset Name	Total Attributes	Attribute Types	Number of ASD Samples			Missing Values Attributes	Missing Values Count
				Total	No	Yes		
1	Children	21	Binary, Continuous and Categorical	292	151	141	age	4
							ethnicity	43
							relation	43
2	Adult	21	Binary, Continuous and Categorical	704	515	189	age	2
							ethnicity	95
							relation	95

3.3 Preprocessing

To ensure data quality and enhance performance of proposed GAT-ANN predictive model, several preprocessing steps were applied to both children and adult ASD datasets. Initially, missing values present in the attributes such as age, ethnicity, and relation were handled using Mean, Median, and Mode imputation strategy. Specifically, continuous attributes were imputed using the mean or median, while categorical attributes were filled using the mode, depending on the nature and distribution of each feature Next, all dataset attributes were converted to binary format to maintain consistency and simplify the input space for GAT-ANN predictive model. This transformation was particularly important for categorical attributes, which were encoded using label encoding technique, depending on their cardinality and relevance. Additionally, the ‘age description’ column, which contained redundant or non-contributory information about age groups was removed from both datasets, as it did not offer any valuable insights for ASD prediction and could introduce bias or redundancy. Using this, a total of 20 attributes were achieved for both the datasets. These preprocessing steps ensured that the data fed into the model was clean, consistent, and suitable for both training and evaluation, forming a reliable foundation for the subsequent phases of the proposed architecture.

3.4 Data Augmentation

In this study, GAN was employed for data augmentation to synthetically expand the training data, considering the Conditional Generative Adversarial Networks (C-GAN) methodology discussed by M. Abedi et al. [22] and M. Mirza et al. [23]. C-GANs are an extension of standard GANs that condition generation process on auxiliary information such as class labels. This is particularly useful in medical data applications, where it is crucial to generate samples corresponding to specific conditions, here, ASD and non-ASD. The C-GANs consist of two neural networks, the generator G and discriminator D, both conditioned on class label y. The generator learns to produce realistic synthetic data $G(z|y)$, where $z \sim p_z(z)$ is a noise vector. In C-GANs, the discriminator tries distinguishing between real data x and generated data $G(z|y)$, also taking y into account. The objective function for C-GAN is given using Eq. (1).

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[logD(x|y)] + \mathbb{E}_{z\sim p_z(z)}\big[\log\big(1 - D(G(z|y)|y)\big)\big] \quad (1)$$

In Eq. (1), x denotes real data sample, z denotes noise vector from latent space, y denotes class label, $G(z|y)$ denotes generator output conditioned on y, $D(x|y)$ denotes discriminator output conditioned on y, $p_{data}(x)$ denotes distribution of real-data, $p_z(z)$ denotes prior distribution of

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noise (Gaussian). The generator G is trained to fool discriminator D, while D is simultaneously trained for correctly classifying real versus generated data, both conditioned on y. In this study, 20% data augmentation was applied using C-GAN to each class in both datasets (children and adults). In this study, only 20% data augmentation was applied to ensure a balanced trade-off between increasing dataset size and maintaining data quality. A higher augmentation rate might introduce noise, redundancy, or over fitting, especially in sensitive medical datasets. By limiting augmentation to 20%, the goal was to enhance the diversity of training data while preserving the original data distribution and minimizing the risk of generating unrealistic or biased samples. This moderate augmentation level allowed for improved model generalization without overwhelming the training process, ensuring meaningful improvements in ASD prediction accuracy and robustness across both datasets. Specifically, additional synthetic samples were generated for both non-ASD and ASD classes for improving class distribution while avoiding over fitting. The dataset summary before and after C-GAN augmentation is presented in Table 3.

Table 3. Dataset Summary Before and After GAN-Augmentation

Dataset	**Class**	**Original Samples**	**Augmented Samples (20%)**	**Total After Augmentation**
Children	ASD	141	28	169
	Non-ASD	151	30	181
Adult	ASD	189	38	227
	Non-ASD	515	103	618

3.5 SMOTE

In this study, SMOTE was used for addressing class imbalance in ASD datasets. This work considered SMOTE because it is a powerful resampling approach which generates synthetic examples for minority class rather than simply replicating existing data points. This improved the GAT-ANN model's ability to learn patterns for underrepresented classes and enhanced prediction performance. The SMOTE works by selecting examples which belong to minority class and synthesizing new instances along line segments joining those examples with their nearest neighbors.

The process of SMOTE is given in Algorithm 1.

Algorithm 1: SMOTE Process	
Input	Preprocessed or GAN augmented data
Output	Class imbalance free training-based feature selection
Step 1	For each minority class sample x_i, the SMOTE identifies KNN using Euclidean distance
Step 2	A random neighbor x_{zi} is selected from KNN
Step 3	A new synthetic sample x_{new} is generated by interpolating between x_i and x_{zi} using $x_{new} = x_i + \delta \cdot (x_{zi} - x_i)$, where x_i is sample from minority class, x_{zi} is one of KNN of x_i and $\delta \in [0,1]$ denotes a random number which determines proportion between points.

In both adult and children ASD datasets, the number of ASD-positive samples (minority) is significantly less than ASD-negative samples (majority). This imbalance leads to biased prediction where model tends to favor majority class. Hence, in this work, the SMOTE helps mitigating issues by increasing number of ASD samples synthetically, improving class distribution and enabling model to better learn minority class patterns. In this work, the SMOTE was applied before feature

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selection in Phase 4 and Phase 5 before classification, to ensure that the learned model is not biased and can generalize well to unseen minority samples.

3.6 Feature Extraction

In this study, a Graph-Based Feature Selection (GBFS) technique was employed to identify the most relevant and informative features for ASD prediction. Unlike conventional feature selection methods discussed in literature survey, the GBFS models feature space as a graph structure where relationships and dependencies among features can be captured more effectively. This method helps retain features that are both relevant to the target class and less redundant with respect to each other. In GBFS, first a feature-graph is constructed using an undirected weighted graph $G = (V, E, W)$, where $V = \{f_1, f_2, \dots, f_n\}$, which denotes set of features, E denotes set of edges between features and W denotes weights of edges indicating similarity. Each node $f_i \in V$ represents feature, and edges E denote similarity or dependency between features. Further, the similarity measure between features is evaluated. For this the weight w_{ij} of an edge between features f_i and f_j is computed using PCC using Eq. (2).

$$w_{ij} = \frac{Cov(f_i, f_j)}{\sigma(f_i) \cdot \sigma(f_j)} \quad (2)$$

In Eq. (2), $Cov(f_i, f_j)$ denotes covariance between features and $\sigma(f_i)$ denotes standard deviation of f_i. Further, the graph is represented using an adjacency matrix A_{ij} as presented in Eq. (3).

$$A_{ij} = \begin{cases} w_{ij}, if\ i \neq j \\ 0 \quad, if\ i = j \end{cases} \quad (3)$$

Further, to measure feature importance, this work has used degree centrality, which is evaluated as presented in Eq. (4).

$$DC(f_i) = \sum_{j=1}^{n} A_{ij} \quad (4)$$

In Eq. (4), $DC(f_i)$ denotes sum of weights of all edges connected to feature f_i. In GBFS, each feature's relevance to target class y is evaluated using Mutual-Information (MI) as presented in Eq. (5).

$$R(f_i) = I(f_i; y) \quad (5)$$

In Eq. (5), $I(f_i, y)$ denotes MI between feature f_i and target label y. The redundancy between two features is evaluated using Eq. (6).

$$Red(f_i, f_j) = I(f_i; f_j) \quad (6)$$

In Eq. (6), $I(f_i; f_j)$ denotes MI between features f_i and f_j. Further, for spectral analysis of graph, Laplacian is computed as $L = \mathcal{D} - A_{ij}$, where $\mathcal{D}$ denotes diagonal degree matrix, which is generated as $\mathcal{D} = \sum_j A_{ij}$. The feature importance score is achieved by combining relevance and centrality as presented in Eq. (7).

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$$Score\ (f_i) = \alpha \cdot R(f_i) + \beta \cdot DC(f_i) \tag{7}$$

In Eq. (7), α and β are tunable parameters controlling importance of relevance and centrality. For ranking features uniformly, the GBGS normalizes the graph score to range of $[0,1]$ using Eq. (8).

$$NScore(f_i) = \frac{Score(f_i) - \min\ (Score)}{\max(Score) - \min(Score)} \tag{8}$$

Finally, the top k features are selected on basis of Eq. (9), where θ denotes threshold value or percentage-based selection and $F_{selected}$ denotes final selected feature set.

$$F_{selected} = \{f_i | NScore(f_i) \geq \theta\} \tag{9}$$

The GBFS provides significant advantages over existing approaches discussed in literature survey by capturing relationships among features through graph structures, considering their dependencies and redundancies. The GBFS balances relevance and redundancy using MI and edge weights, ensuring that selected features contribute meaningfully to classification. The method preserves the data's structural integrity using spectral properties. By reducing irrelevant features, it enhances model performance, improves accuracy, and minimizes over fitting. In this study, it was applied in Phases 2 to 7 to refine inputs for the GAT-ANN model.

3.7 Graph Attention Network Artificial Neural Network Model

In this section, a novel model is proposed for ASD prediction by integrating GAT with ANN. The GAT is used to address class imbalance and extract high-level feature representations through graph-based attention, while the ANN serves as the final classifier. The GAT-ANN ensemble model, leverages the graph structure of feature space and the learning capability of ANN to achieve robust classification performance, particularly in imbalanced datasets such as those seen in ASD diagnosis. Consider input feature space be represented as graph $G = (V, E)$, where V denotes set of feature nodes and E denotes set of edges representing correlation between features. In GAT, first, the features from GBFS are transformed linearly using Eq. (10).

$$h'_i = W h_i \tag{10}$$

In Eq. (10), h_i denotes input feature vector of node i, W denotes trainable weight matrix for linear transformation, h'_i denotes transformed feature of node i. Further, an attention coefficient between the nodes is evaluated using Eq. (11).

$$e_{ij} = LeakyReLU(a^T [h'_i || h'_j] \tag{11}$$

In Eq. (11), e_{ij} denotes raw attention score between nodes i and j, a^T denotes learnable attention vector,$||$ denotes concatenation operator and $LeakyReLU$ denotes activation function for non-linearity. Further, the attention coefficient is normalized using $Softmax$, which is evaluated using Eq. (12).

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}(i)} \exp(e_{ik})} \tag{12}$$

In Eq. (12), α_{ij} denotes normalized attention score and $\mathcal{N}(i)$ denotes neighborhood of node i. The aggregation of neighboring features is further evaluated using Eq. (13).

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$$h_i^{attn} = \sigma\left(\sum_{j\in\mathcal{N}(i)} \alpha_{ij} h_j'\right) \tag{13}$$

In Eq. (13), h_i^{attn} denotes updated node representation using attention-weighted aggregation and σ denotes activation function $ReLU$. For addressing class imbalance, the GAT learns node (feature) relevance by emphasizing minority-class features through attention weights. The attention weights are guided to focus more on patterns that frequently occur in minority class. This method reduces bias toward majority class without oversampling. The imbalance-aware attention scaling in GAT is done using Eq. (14).

$$\tilde{\alpha}_{ij} = \frac{\alpha_{ij}}{\log(1 + f_j)} \tag{14}$$

In Eq. (14), $\tilde{\alpha}_{ij}$ denotes adjusted attention score and f_j denotes frequency of class occurrence for feature j. Finally, the output of GAT layer is passed to a feed-forward ANN for classification as presented in Eq. (15).

$$z = ReLU(W_1 h_i^{attn} + b_1) \tag{15}$$

In Eq. (15), z denotes output of first ANN hidden layer, W_1, b_1 denotes weight and bias for hidden layer. The final prediction output is evaluated using Eq. (16).

$$\hat{y} = Softmax(W_2 z + b_2) \tag{16}$$

In Eq. (16), $\hat{y}$ denotes predicted probability distribution over ASD and non-ASD classes, W_2, b_2 denotes weights and biases for output layer. Further, the loss function used in GAT-ANN is evaluated using Eq. (17).

$$\mathcal{L} = \mathcal{L}_{CE} + \lambda \sum_{i,j} \left(\alpha_{ij} - \bar{\alpha}\right)^2 \tag{17}$$

In Eq. (17), $\mathcal{L}_{CE}$ denotes cross-entropy loss, $\bar{\alpha}$ denotes mean attention-score and λ denotes regularization coefficient. The proposed GAT-ANN model combines the interpretability of graph attention mechanisms with the classification power of ANN. By utilizing feature graph from GBFS and applying attention, the model identifies and emphasizes feature interactions that are most relevant to ASD cases, especially under class imbalance. This avoids over fitting caused by synthetic oversampling and provides understanding of feature importance. Using GAT, minority-class feature patterns are effectively learned through adaptive attention scaling. The ANN then maps the refined, imbalance-aware features to the target prediction. Together, the model achieves high accuracy and robustness, particularly valuable in medical settings like early ASD diagnosis where class imbalance and feature relevance are critical. The performance metrics used in this study are discussed in detail in next section.

3.8 Performance Evaluation

The standard performance metrics were used for evaluating the ensemble GAT-ANN model. The metrics include accuracy, precision, recall and f-score which were evaluated using Eq. (18)-Eq. (21), where FP denotes false-positive, FN denotes false-negative, TP denotes true-positive and TN denotes true-negative.

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$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

$$Precision = \frac{TP}{TP + FP} \tag{19}$$

$$Recall = \frac{TP}{TP + FN} \tag{20}$$

$$F - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{21}$$

In the next section, the results of the GAT-ANN are discussed in detail.

4 Results and Discussions

To evaluate the performance of proposed ensemble GAT-ANN model for ASD prediction in children and adults, experiments were conducted on a system with an Intel i7 processor and 16GB RAM. The model was implemented in Python using appropriate libraries. The datasets used are described in Section 3.2, and performance metrics are detailed in Section 3.8. This section presents the evaluation results of the GAT-ANN model under two scenarios: without handling class imbalance and with class imbalance handling. Additionally, a comparative analysis with existing models is provided, followed by an ablation study to assess individual model components as discussed in Section 3.1.

4.1 Performance Study of ASD Datasets without handling class imbalance

For this study, the preprocessed children and adult dataset were considered, where GBFS was used for feature selection. The performance results of GAT-ANN model on ASD datasets without applying any class imbalance handling is presented in Figure 2. As shown in the evaluation metrics, the model achieved 100% accuracy, precision, recall, and F-score on both the children and adult ASD datasets. These results suggest that the model was able to perfectly differentiate between ASD and non-ASD cases across both datasets. This level of performance indicates that the proposed architecture is highly capable of learning intricate patterns in the data and making precise classifications. However, achieving 100% across all metrics, particularly without addressing class imbalance, also points towards potential data bias.

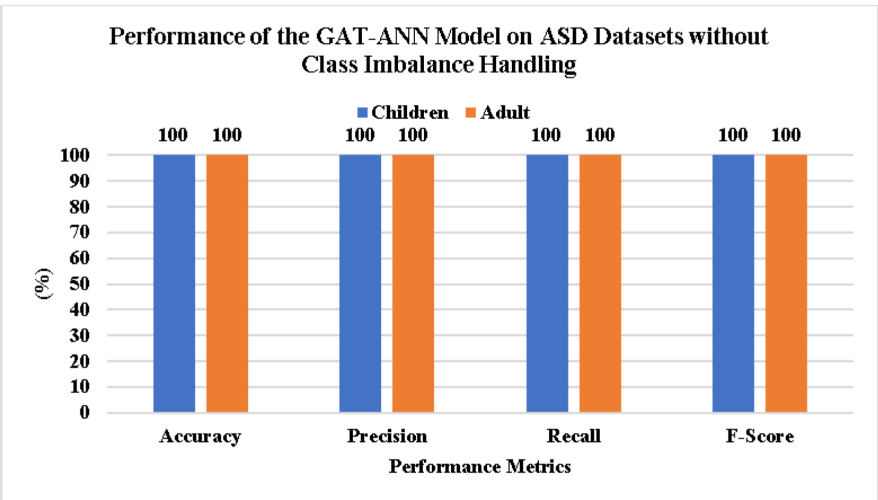

Figure 2. GAT-ANN Model Performance on ASD Datasets with Class Imbalance Handling.

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4.2 Performance Study of ASD Datasets with handling class imbalance

For this study, the preprocessed children and adult dataset were considered, where GBFS was used for feature selection. The performance of the GAT-ANN model on ASD datasets after applying class imbalance handling is presented in Figure 3. For children dataset, the model achieved 99.986% accuracy, 99.984% precision, 99.985% recall, and a 99.985% F-score. Similarly, for the adult dataset, the model attained 99.991% accuracy, 99.989% precision and recall, and a 99.990% F-score. These results show that even after addressing the inherent class imbalance, often a significant challenge in medical datasets, the model maintained better predictive performance. The minimal drop from perfect scores observed without class imbalance handling suggests that the model was not over fitting and is capable of learning from more realistic, balanced datasets. Moreover, the consistent values across all metrics show that the model is not biased towards any class, ensuring fair and reliable predictions for both ASD and non-ASD cases. This validates the effectiveness of the GAT-ANN ensemble approach in accurately detecting ASD across different age groups.

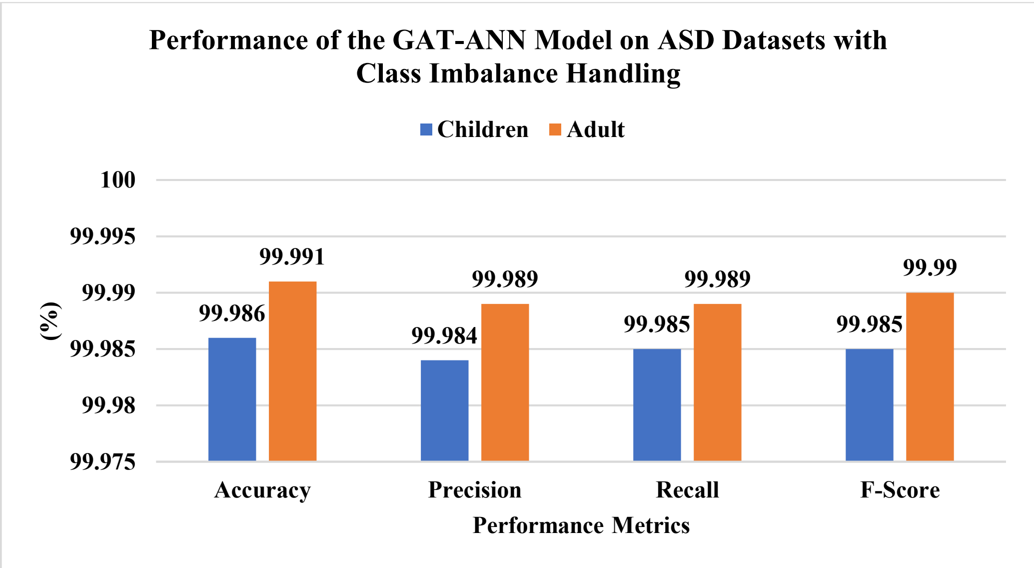

Figure 3. GAT-ANN Model Performance on ASD Datasets with Class Imbalance Handling.

4.3 Comparative Study

The comparative performance analysis is presented in Tables 4 and Table 5, which highlights good performance of GBFS+GAT-ANN model in predicting ASD for both children and adult datasets. On the children dataset, the proposed model achieved an accuracy, precision, recall, and F-score of 99.98%, outperforming most existing methods, including traditional ML models such as DT, LR, SVM, and RF [10], [14], [19], which although reached 100% accuracy, lacked class imbalance handling and feature selection. While some ensemble methods like the one in [18] using SL-SMOTE also performed well (accuracy 99.68%, F-score 99.27%), they still did not reach the same level of uniformity across all metrics as GAT-ANN. For the adult dataset, the GAT-ANN model similarly demonstrated good performance with 99.99% accuracy and 99.98% across other metrics, slightly outperforming the best existing model [18] which used SL-SMOTE and achieved 99.89% accuracy. Most other methods [11], [12], [14] showed relatively lower performance, often suffering from imbalance or lack of advanced feature selection. The consistency and robustness of GAT-ANN is attributed to integration of GBFS and GAT, which enhances representation learning by capturing inter-feature dependencies and effectively handling class imbalance.

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Table 4. Comparative Performance Analysis on the Children ASD Dataset

Ref	Model	Accuracy	Precision	Recall	F-Score	Feature Selection	Class Imbalance
[10]	DT	100	100	100	100	No	No
	LR	100	100	100	100		
	SVM	100	100	100	100		
	NB	94.2	94.68	94.44	94.24		
	KNN	97.7	97.72	97.77	97.69		
	RF	100	100	100	100		
[11]	LR	98	92	44	60	Yes	No
	SVM	99	97	58	73		
[12]	GNB	93	100	88	98	Yes	No
	BNB	93	94	94	94		
	MNB	76	82	72	77		
	SVM	64	100	34	51		
	RF	100	100	100	100		
	QDA	54	54	50	70		
[14]	NB	94.25	90.91	97.56	94.12	Yes	No
	KNN	86.21	87.18	82.93	85		
	SVM	100	100	100	100		
	RF	96.55	93.18	100	96.47		
	DT	87.36	87.5	85.37	86.42		
	XGB	97.7	97.56	97.56	97.56		
	LR	100	100	100	100		
	ANN	98.85	97.62	100	98.8		
[18]	Ensemble+SL-SMOTE	99.68	99.99	98.28	99.27	Yes	Yes
[19]	LR	100	100	100	100	No	No
	KNN	98	98.5	97.5	98		
	SVM	100	100	100	100		
	DT	100	100	100	100		
	RF	100	100	100	100		
	GBFS+GAT-ANN	**99.98**	**99.98**	**99.98**	**99.98**	**Yes**	**Yes**

Table 5. Comparative Performance Analysis on the Adult ASD Dataset

Ref	Model	Accuracy	Precision	Recall	F-Score	Feature Selection	Class Imbalance
[10]	DT	100	100	100	100	No	No
	LR	100	100	100	100		
	SVM	95.2	96.98	90.9	93.44		
	NB	97.6	96.67	97.21	96.94		
	KNN	97.7	93.2	90.53	91.75		
	RF	100	100	100	100		
[11]	LR	81	73	56	63	Yes	No
	SVM	78	81	51	62		
[12]	GNB	96	94	91	93	Yes	No
	BNB	95	89	91	90		
	MNB	85	76	56	64		

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	SVM	84	100	35	52		
	RF	100	100	100	100		
	QDA	95	94	85	89		
[14]	NB	96.19	95	91.94	93.44	Yes	No
	KNN	89.05	84.21	77.42	80.67		
	SVM	96.19	93.55	93.55	93.55		
	RF	95.71	94.92	90.32	92.56		
	DT	87.14	84.31	69.35	76.11		
	XGB	96.19	95	91.94	93.44		
	LR	97.14	96.67	93.55	95.08		
	ANN	96.67	91.04	98.39	94.57		
[18]	Ensemble+SL-SMOTE	99.89	99.98	99.97	99.98	Yes	Yes
	GBFS+GAT-ANN	**99.99**	**99.98**	**99.98**	**99.98**	**Yes**	**Yes**

4.4 Ablation Study

The ablation study presented in Table 6 and Table 7 shows impact of different components presented in the architecture (Figure 1). The components include usage of feature selection, usage of SMOTE, GAN-based augmentation and GAT-based class imbalance handler on performance of GAT-ANN model for children and adult ASD dataset. In Table 6, for children dataset, the GAT-ANN performance significantly improves using GBFS and GAT imbalance handling, achieving 99.98% accuracy (SL. No 3). Further, the inclusion of SMOTE and GAN, shows 99.27% accuracy (SL No. 5). Further, combining GAN augmentation and GAT imbalance handler, even without SMOTE or GBFS showed 99.53% accuracy, showing better results (SL No. 6). Further, the best results are achieved using feature selection, GAN augmentation and GAT imbalance handler, achieving 99.98% accuracy (SL. No 7).

Table 6. GAT-ANN model ablation study for Children ASD dataset.

SL. No	Feature Selection	SMOTE	GAN Augmentation	GAT Class Imbalance Handler	Accuracy	Precision	Recall	F-Score
1	No	No	No	No	94.23	93.55	94.89	94.22
2	Yes	No	No	No	**100**	**100**	**100**	**100**
3	Yes	No	No	Yes	**99.98**	**99.98**	**99.98**	**99.98**
4	Yes	Yes	No	No	98.92	98.55	98.60	98.57
5	Yes	Yes	Yes	No	99.27	99.00	99.05	99.02
6	No	No	Yes	Yes	99.53	99.45	99.38	99.41
7	Yes	No	Yes	Yes	**99.98**	**99.98**	**99.98**	**99.98**

In Table 7, for the adult dataset, baseline performance without any enhancements is 92.11%. With GBFS and the GAT handler alone achieved 99.99% accuracy (SL No. 3). Further, using GAN augmentation (SL. No 5) further boosted performance, while combination of GAN and GAT handler (SL. No 6) achieved 99.63% accuracy. The best performance 99.99% across all metrics, occurs when all enhancements are combined (SL. No 7), validating the effectiveness of the full pipeline.

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Table 7. GAT-ANN model ablation study for Adult ASD dataset

SL. No	Feature Selection	SMOTE	GAN Augmentation	GAT Class Imbalance Handler	Accuracy	Precision	Recall	F-Score
1	No	No	No	No	92.11	90.24	91.87	91.05
2	Yes	No	No	No	**100**	**100**	**100**	**100**
3	Yes	No	No	Yes	**99.99**	**99.98**	**99.98**	**99.99**
4	Yes	Yes	No	No	97.95	97.53	97.40	97.46
5	Yes	Yes	Yes	No	98.48	98.31	98.10	98.20
6	No	No	Yes	Yes	99.63	99.48	99.50	99.49
7	Yes	No	Yes	Yes	**99.99**	**99.98**	**99.98**	**99.98**

5 Conclusion

In this study, a novel ensemble DL approach, GAT-ANN, was proposed for accurate prediction of ASD in children and adults. This work highlights the increasing prevalence of ASD and the challenges associated with its early and accurate diagnosis using conventional methods. A key issue identified was presence of class imbalance across existing ASD datasets, which hampers performance of traditional and even some ML models. Additionally, a lack of focus on hybrid DL models leveraging structural relationships within data formed a significant research gap. To address these challenges, the study defined a clear problem statement, to develop an effective model that improves ASD prediction accuracy by integrating advanced feature selection, class imbalance handling, and DL strategies. The objectives included enhancing prediction performance, reducing bias from imbalanced datasets, and improving applicability. The proposed methodology incorporated GBFS for feature selection, SMOTE and GAN-based data augmentation for class balancing, and a novel ensemble GAT-ANN architecture. GAT enabled effective relationship learning among data features, while ANN enhanced classification. Experimental results revealed significant performance improvements. The GAT-ANN model achieved 99.98% and 99.99% accuracy for children and adult datasets. Ablation studies further validated each module's contribution to the overall performance. In conclusion, the GAT-ANN model demonstrates high predictive capability for ASD. Future work can explore Graph Convolutional Neural Networks (GCNNs) to better capture spatial relationships, further enhancing predictive accuracy and model robustness.

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Data Availabiliyty

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