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A NOVEL AUTISM SPECTRUM DISORDER DETECTION USING MULTI-LABEL GRAPH CONVOLUTIONAL NETWORK WITH LABEL ATTENTIVE NEIGHBORHOOD CONVOLUTION

Abstract. Due to the lack of precise medical testing for autism, such as blood tests to detect the illness, diagnosing autism spectrum disorder (ASD) has proven to be challenging. The prevalence of restrictive and/or repetitive behaviors and difficulties and impairments in social communication are hallmarks of autism spectrum disorders. This behavioral condition has been identified. Doctors assess the child's developmental history and behavior to make a diagnosis. **Research results.** This research used a hybrid Multi Label-Graph Convolutional Network (ML-GCN) with label-attentive neighborhood convolution to categorize the autism spectrum disorder. It offers a clear and effective graph wrapper module in particular for collecting the local attribute data of a specific node to produce a logical representation of node functioning. Additionally, the homeopathic theory recommends developing a taxonomy for attention-related terms. Furthermore, developed an adaptive graph technique that allows the model to learn the kernel for each layer dynamically and uniquely, allowing the model to acquire more valuable and efficient features. On three frequently used reference datasets, including customized and non-specialized networks, comprehensive tests were conducted to validate the neural network-based approach to multi-label classification.

Keywords: Autism Spectrum Disorder; Graph Convolutional Network; Label attentive neighborhood convolution; Accuracy; decision support information system.

Introduction

Autism spectrum disorder (ASD) is becoming more prevalent among persons of all ages. Early identification of this neurological disorder can help patients keep their physical and mental well-being [1]. This aspect has heightened interest in uncovering and researching issues related to autism spectrum disorders in an attempt to create therapeutic alternatives. It might be difficult to diagnose autism spectrum disorder (ASD) since symptoms of various mental conditions are similar to those of autism spectrum disorder (ASD) [2]. Autism spectrum disorder (ASD) is an increasing issue for people of all ages these days. Early identification of this neurological disorder can help patients preserve their physical and emotional well-being. This factor has boosted interest in detecting and investigating difficulties connected with autism spectrum diseases in an attempt to create therapeutic alternatives [3]. Autism spectrum disorder (ASD) can be challenging to diagnose because several psychiatric illnesses exhibit symptoms comparable to ASD [4]. They examined the behavior of heart rate (HR) and intracranial pressure (ICP) in critically damaged pediatric patients using multiple computer models. The researchers intended to look into and assess the association between HR and ICP in pediatric patients who had been in a traumatic event [5]. In this investigation, patients reported considerable overlap and interaction signs between HR and ICP. Several researches have been undertaken to use deep learning algorithms to classify neuroimaging image data for ASD diagnosis [6]. Deep learning has also benefited from MRI and EEG investigations. The fundamental purpose of the project is to develop a solution for ASD classification and diagnosis using machine learning, data transmission, and thematic handwriting analysis [7]. The proposed using transfer learning to categorize ASD and non-ASD participants based on data gathered through handwriting manipulation in this research.

Motivation

This research will apply a popular technique for capturing label space topology known as graph modeling to account for nested label dependencies. For classification purposes, this research specifically describes it as a label word comprising each graph node (label) and utilizes GCN to directly transfer these connected elements to a set of related classifiers. These classifiers can then be applied directly to image elements. The creation of GCN-based models is impacted by two factors. First, the trained classifier can keep a weak semantic structure in an embedding space full of semantically significant concepts since the display options it includes are common to all classes.

Literature Survey

The Swarm Intelligence-based ASD diagnostic dataset, which includes 21 features from the UCI Machine Learning Repository, was used in this research, a model-based autism detection technique, to test a binary wrapper for Firefly feature selection [8]. Experiments have shown that machine learning models can enhance classification accuracy on a small collection of features [9]. In the ASD dataset, discovered that 10 out of 21 variables were sufficient to identify ASD from non-ASD patients using the swarm intelligence-based dual-purpose Firefly feature selection framework [10]. This technique produced average accuracies ranging from 92.12% to 97.95%, confirming the hypothesis that the best feature selection produced around the same average accuracies as the total ASD diagnosis dataset [11]. Several research publications have employed machine learning in diverse techniques to improve and accelerate autism spectrum disorder diagnosis. ADHD autism is defined using a combination of advanced feature selection and sampling on the 65-item Social Response Scale [12]. Measures of brain activity are used to forecast ASD. Additionally, employed are soft computing techniques such as classifier ensembles, ANNs, and probabilistic inference [13]. Many experiments have been carried out with machine learning models that simply use features as input qualities. Neuroimaging data is also used in some investigations [14].

Automated assessments on the identical topic were 86.5 percent more accurate than assessments given by health experts. The suggested machine learning classification was built utilizing data obtained from young people during social interactions [15]. Although the aforesaid approach produces excellent outcomes, it is dependent on the subjects' social interactions and the environment in which the practitioners must prepare [16].

The imitation method was used to identify adults with autism using a machine-learning classifier [17]. The goal of this research was to look at potential set-up issues with mechanical assemblies and discrimination tests [18]. This dataset includes 16 ASC individuals who used various hand movements. Using machine learning methods, 40 movement constraints were discovered from eight simulated scenarios [19]. This research describes how machine learning techniques were used to evaluate high-dimensional data and categorize autism diagnoses in small samples [20]. The previous part highlighted the possibilities of utilizing deep learning-based models to detect ASD in the population [21]. Because the majority of the works discussed above employ a typical machine learning approach, their performance is limited. This research, contrasted one particular deep learning model's performance with that of numerous machine learning models [22].

Problem Formulation

Disorders on the autism spectrum affect how the human brain develops. Autism spectrum disorder patients frequently struggle to socially engage and communicate with others. In this sense, life typically has an impact on a person's entire existence. It's interesting to note that the condition is influenced by both environmental and hereditary variables. The issue can manifest as early as age 3 and have lifelong symptoms. Patients with this condition cannot be fully healed, although if symptoms are occasionally recognized, their effects can be temporarily lessened. Since they believe that the ailment is caused by human genes, researchers have not yet been able to determine the precise cause of autism spectrum disorder. Environment and development are influenced by human genes. ASD is affected by various risk factors, including low birth weight babies, siblings who also have the disorder, and older parents.

Proposed work. The pipeline requires a function for each node of the graph as well as the original population graph as input. The train CNN graph model is then called on a collection of randomly generated graph implementations. These neural networks' output layer uses a softmax function to determine each node's class-related probability. The consensus module then creates the final class labels by incorporating community decisions.

Methodology

The system's general functionality and flow are depicted in Fig. 1.

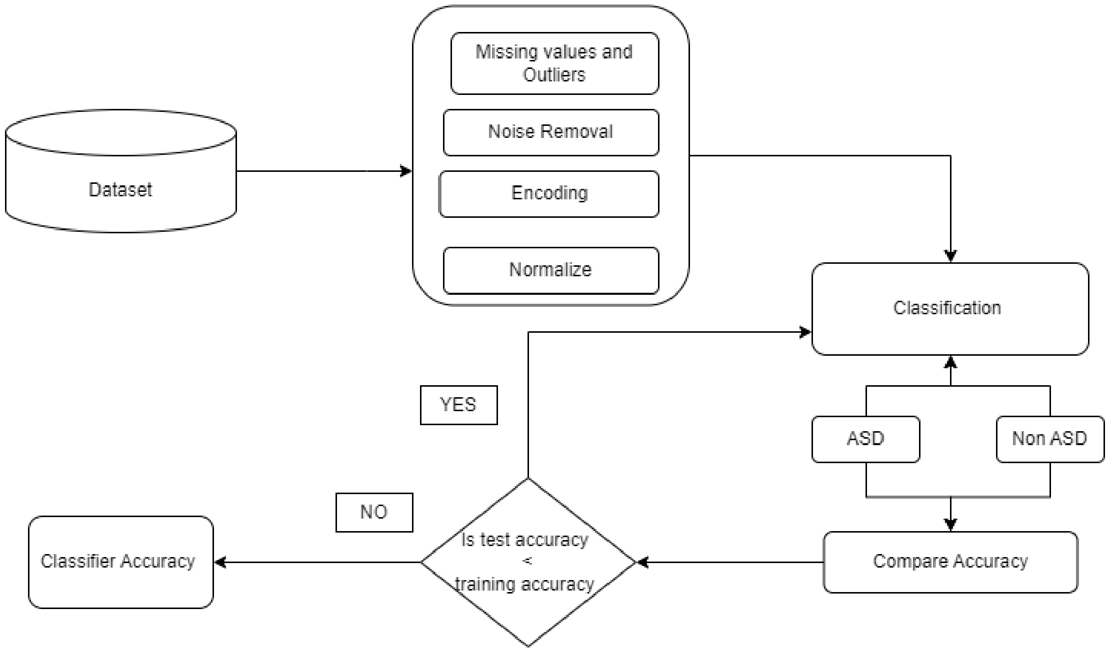


Fig. 1. Workflow of the proposed algorithm

The dataset is first preprocessed to eliminate noise, missing values, and outliers. Categorical properties are then encoded. Additionally, employ feature engineering to choose the dataset's most advantageous features out of all those that are offered. This decreases the data's dimensionality, speeding up and improving the effectiveness of the training process. The classification algorithm is represented by an ML-CGN classifier and used to predict the output label (ASD or no ASD) after the dataset has been preprocessed.

Multi-Label Graph Convolutional Network (ML-GCN). The proposed method presents a unique multi-label GCN (ML-GCN, Fig. 2) based model in this research to capture label associations for multi-label image recognition, although it is not feasible due to the scalability and flexibility of competing approaches. This research suggested learning interdependent object classifiers on previous label representations rather than learning object classifiers as independent parameter sets. To explicitly characterize label dependencies for classifier training, additionally create an effective label connectivity matrix for controlling information propagation between nodes in GCNs. The proposed reweighting technique is used to update a node's resources that evenly distribute weights between a node and its neighbors, therefore lowering the balance between adaptability and excess.

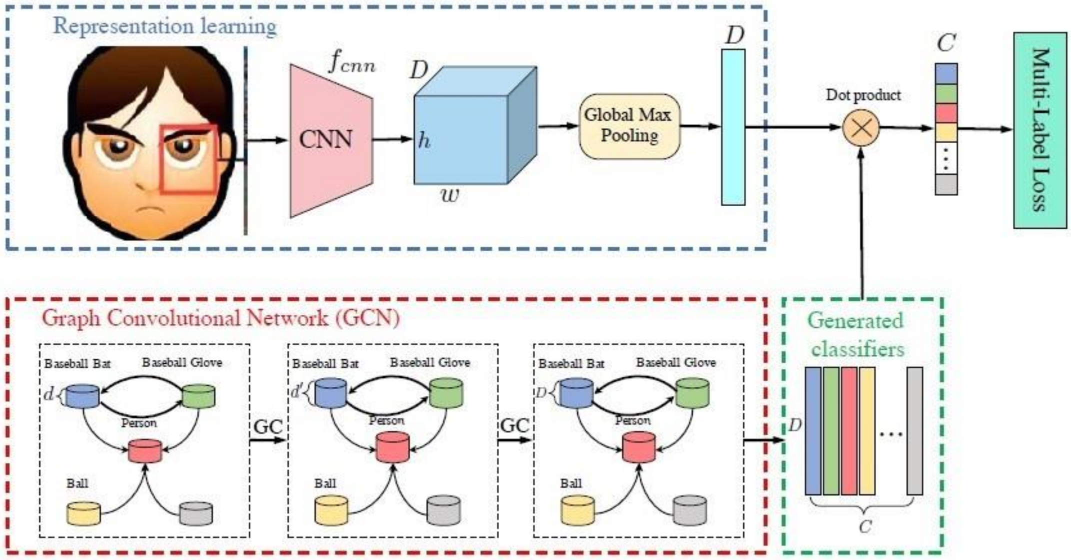


Fig. 2. Proposed ML-GCN Model

Except for the addition of 19 layers, the VGG19 model, also known as VGGNet-19, is fundamentally similar to the VGG16 model. The numbers "16" and "19" represent the model's total number of weighting layers (convolutional layers). In terms of the number of convolutional layers, VGG19 is more advanced than VGG16. For example, ResNet is made up of five layers, each of which halves the resolution, resulting in a final feature map that is 1/32 * 1/32 in size. In contrast, the icons in CNN are originally set to 16x16, which decreases the resolution at that size. The last layer, on the other hand, preserves the exact precision. In VGG, convolutional layers employ the smallest allowable domain, denoted by 3*3, and the smallest size that may incorporate left/right and top/bottom information. There are 11 convolution filters as well, each of which performs a linear transform function on the input.

ML-GCN propagates information between nodes using a correlation matrix. As a result, building the correlation matrix is a critical task for GCN. Although they are typically specified for applications, correlation matrices are typically absent from multi-label image recognition datasets. The approach's structure can be broken down into three steps. In the first step of the approach, the dataset is preprocessed to reduce noise and improve image quality. It is critical to note that the primary goal of employing several models is to run a series of tests to get the best outcomes. The third and final stage before employing the softmax function is to classify the pictures using pooling and dropout layers to avoid overfitting. This is the previous stage. Convolutional neural networks and hybrid feature extraction have considerably enhanced deep learning performance in modern vision applications. This highlights the importance of learning a diverse set of visual representations for efficient delivery and good performance, in part because convolutional layers encode spatial equivalence, which adds considerable biases.

In general, ML-GCN-based image categorization networks transmit representations with lesser accuracy. For example, ResNet is made up of five layers, each of which halves the resolution, resulting in a final feature map that is 1/32 * 1/32 in size. In contrast, the icons in ML-GCN are originally set to 16x16, which decreases the resolution at that size. The last layer, on the other hand, preserves the exact precision. As a result, ML-GCN is more likely than ResNet to keep position data.

The best model is saved where the loss value is the lowest after being trained using data from all subjects at the site. The encoder output vector is produced by feeding the autoencoder a one-dimensional function link vector, a compact vector that represents each of the object's distinct qualities. The mean vector of the individual feature vectors of all participants at each site was determined by aggregating the site means to further develop feature vectors that can reflect information on variations between sites. The explanation is that it utilizes an average of the specific traits of the site's themes to reflect the traits of the entire site. Fig. 3 illustrates the Label attentive neighborhood convolution (LANC).

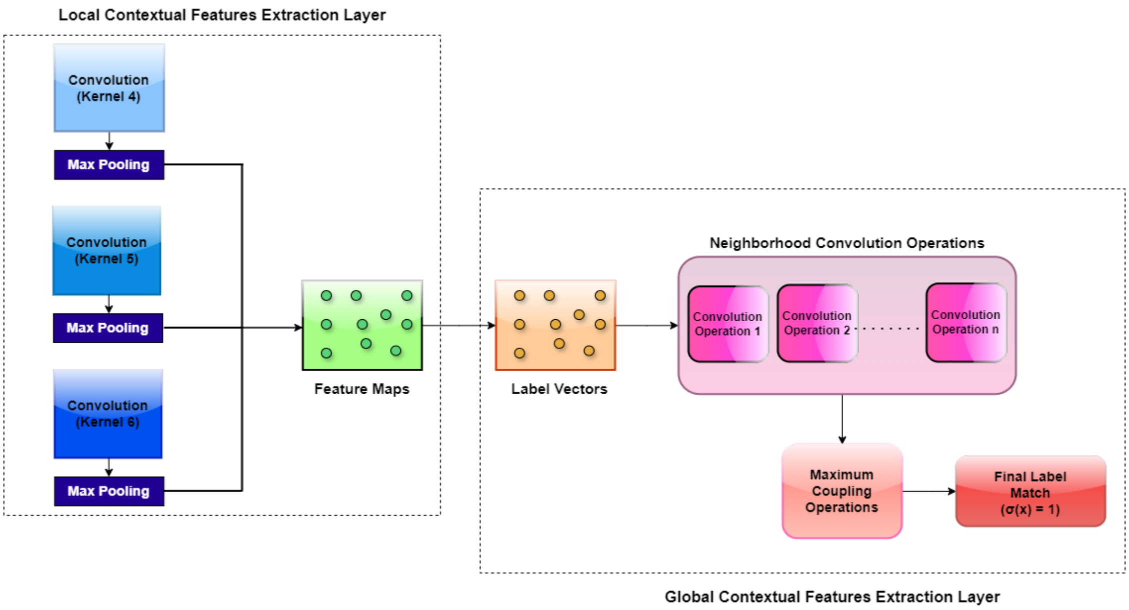


Fig. 3. Label attentive neighborhood convolution

The aforementioned convolution operators serve as the fundamental building blocks of neighborhood convolution schemes, which allow for the run-time specification of several kernels with various window widths h. However, because of the maximum coupling operation, the length of the final feature vector only depends on the number of kernels or channels. The length of the feature map is proportional to the number of rows M and the kernel window size h. The size of a specific node's neighborhood or starting feature vector has no bearing on the size of the node's final representation vector. To compute dependencies between node feature vectors and label inclusion vectors, labels are also included in the vector space. The final label match is determined by converting the outcomes generated by each output node into probabilities using the sigmoid function. The overall framework of the model is depicted in the Fig. 4.

The foundation of the ML-GCN-LANC project will be GCN. GCN is suggested for semi-map classification, with node-level output being the prediction score of each node. Otherwise, each ML-GCN-LANC node builds a label classifier that is appropriate for the task as its final output. In addition, graph appearance is typically predefined in other tasks and not mentioned in multi-label picture selection tasks. The correlation matrix must therefore be created from scratch. The training modules for the GCN classifier and the image representation are the two key modules that make up the method's overall structure, which is depicted in the figure. In ML-GCN-LANC, a node's qualities are weighed based on both those of the node and those of its neighbors. The potential for excessive homogeneity in binary correlation matrices is a second obvious issue. This means that node features can be smoother than nodes from different groups.

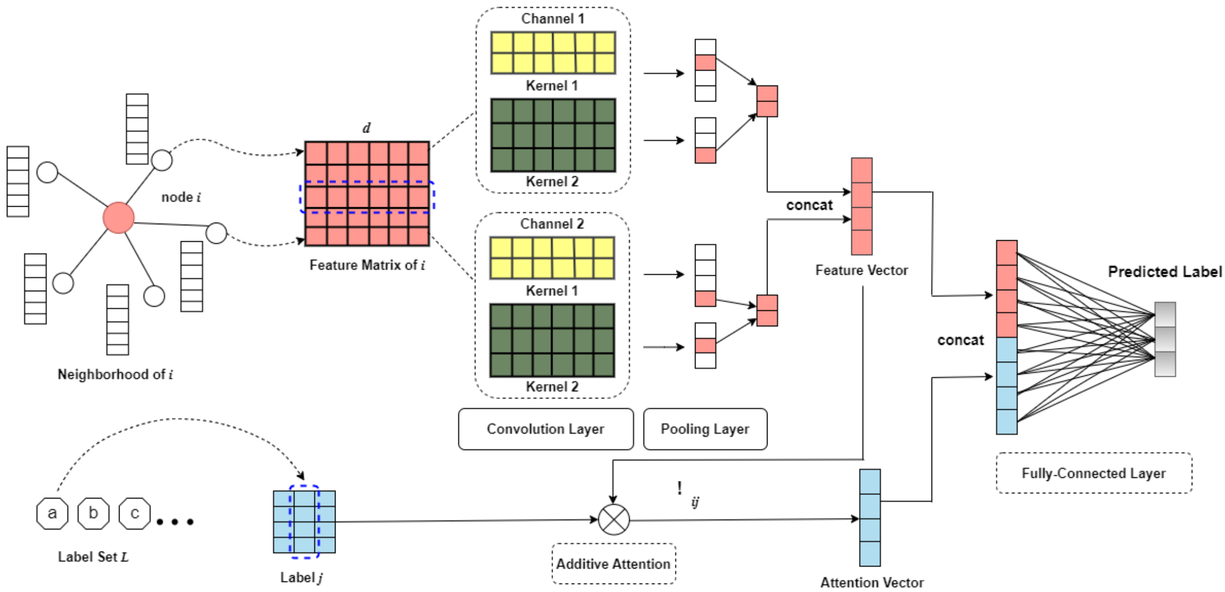


Fig. 4. ASD prediction Hybrid Model of Multi-Label Graph Convolutional Network with label attentive neighborhood convolution (ML-GCN-LANC)

Materials and Methods

The following datasets were used in this research: (1) the UCI Child Autism Dataset, (2) the UCI Adolescent Autism Dataset, and (3) the UCI Adult Autism Dataset.

Dataset. The datasets accessed for this research's purposes came from one of three open UCI repositories: [12], [15], or [16]. They primarily employed three types of datasets in the investigation. The first dataset, which has 292 cases and 21 attributes, is about screening for ASD in young children. The second dataset, which relates to adult ASD screening, has 21 features and 704 cases. There are 104 cases and 21 features in the third dataset on teenage ASD. The parameters for ML-GCN-LANC are 0.01 learning rate, 200 maximum epochs, 16 hidden units, and 0.5 dropout. The training set, verification set, and test set are the three segments that make up the three data sets. The split ratio is set to 3:3:4, the embedding vectors for the node attributes are produced at random, and the vector size is set to 128. There are two sections to the entire dataset. With an 80:20 ratio, one is the training dataset and the other is the testing dataset.

Simulation Parameters setting. To know the size of each node's neighborhood, which is the number of rows M, to build the matrix M for each node. Because the amount of node attributes is constant across datasets, the number of columns M equals the number of node attributes. The range of the convolution kernel size is [2–5]. Sort the 16 cores by size. Therefore, the node feature vector size is 64 following convolution and addition operations. A marker association network based on co-occurrence in samples is built to achieve the initial inclusion of markers.

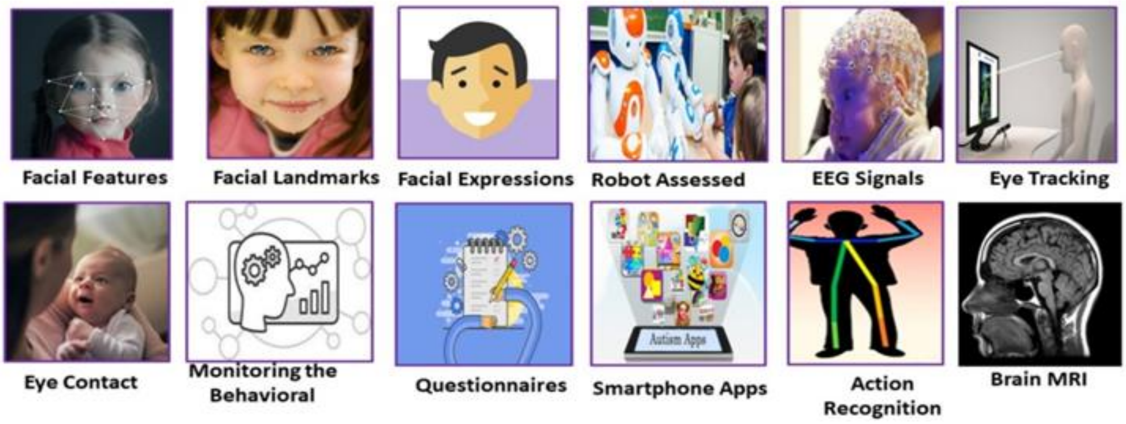


Fig. 5. Example of Autism dataset

To validate a diagnosis of autism spectrum disorder, data points from the answer set are gathered and sorted into one of four categories: A true positive (TP) is a person with autism who has been correctly diagnosed as such. A true negative (TN) indicates that the respondent is not autistic and that the response dataset wrongly categorized them as nonverbal. False positive responses (FPs) are reactions that wrongly categorize non-ASDs as having ASD. When someone is misdiagnosed as not having autism spectrum disorder, they are classified with autism spectrum disorder (ASD). Whereas recall is the number of autism cases properly identified out of all instances where autism was present.

Performance Evaluation metrics

After setting up the experimental paradigm, reviewed the training graph for each training run to ensure that no overfitting happened. A complete selection of all adult, child, and adolescent ASD screening data was made from the findings of several machine learning algorithm methodologies. To assess the predicted model's specificity, sensitivity, and accuracy, all 21 features were chosen.

The proposed ML-GCN-LANC model was implemented in the Python 3.7 environment. To build the deep learning-related models, applied Keras (2.2.4) package with TensorFlow (1.13.1) backend. The experiments were conducted on a workstation with 10 cores of Intel Core i9 CPU and 64 GB RAM. Due to the high computation cost of the deep learning algorithm, this research configured one GPU (Nvidia TITAN Xp, 12 GB RAM) to accelerate the training speed of the models. The proposed method implementation, Kernel has been used with 0.1 gamma value, Adam Optimizer with 0.0001 learning rate and 100 epoch, RMSprop Optimizer used.

The training time parameters for the models were as follows: Logistic Regression took approximately 5 minutes per dataset, SVM took approximately 15 minutes per dataset, CNN took approximately 20 minutes per dataset, Xception took approximately 30 minutes per dataset, NASNetMobile took approximately 40 minutes per dataset, and the Proposed ML-GCN-LANC took approximately 9 minutes per dataset. This proves that the proposed model ML-GCN-LANC is fairly efficient and achieved a better accuracy within a limited training period and hence can be effectively implemented for real-life scenarios.

Three different datasets like Adult dataset ASD, children ASD, and the Adolescent dataset are used for evaluation (Table 1). An F1 score of 0.5 or greater is deemed satisfactory. Although LR produces comparable results, ML-GCN surpasses CNN. It may be deduced from the findings that ML-GCN and CNN predict autism more correctly than other ML models that employ feature datasets and can be used to detect autism early.

Table 1 – **ASD prediction matrix**

Detection	Person with ASD	Person without ASD
ASD detected	TP	FP
ASD not detected	FN	TN

Autism cases are predicted accurately and recall shows the number of correctly identified autism cases among all autism cases. Following a thorough examination, it was determined that the ML-GNN models are more suited for diagnosing autism in both children and adults. The doctors can predict ASD with up to 99% accuracy. The proposed model's performance was also compared to other models previously proposed in the literature.

For the first time, an OOST (out-of-sample test) index was created using autism data. This metric measures how well the model predicts samples on which it has not been trained (i.e., brand-new test data). When the OOST has fewer erroneous predictions (FP and FN), the model becomes more flexible. According to the table results, the OOS indicator has nearly no misclassifications across all age groups. In terms of classification performance, even aggressive feature selection models beat feature selection models based on validation data. The method's accuracy was determined using 10-fold cross-validation. However, because the majority of the results for the sub-dataset show a high accuracy of around 100%, the authors attempted to demonstrate the following. Use the dataset to run the AutoML model. When all features are included, the AutoML model predicts a subset of the data with near-perfect accuracy. Since there was no previous literature on AutoML models for classifying autism based on non-clinical data, and most of the available literature provides accuracy only using classical and deep learning models, the authors structured their research by comparing performance.

To analyze the performance of GoogleNet as the research's basis model, the pre-processed data for the research comparison was trained with multiple CNN models. For each activity (drawing a circle, drawing a triangle, writing a number, and so on), train a new network and label participants for testing using the intermediate labels obtained from this network (18 in total). Alexnet, Resnet 18, VGG 16, and Squeeze Net are some of the models tested. All 5-fold cross-validation ML-GCN-LANC models have the same train-to-test dataset ratio as tabulated in Table 2.

Table 2 – **Performance metrics of ASD children dataset**

Classifier	Speci-ficity	Sensi-tivity	Accuracy (%)	F1-score
Logistic Regression	86.26	87.13	88.58	86.86
SVM	91.68	91.79	92.21	91.29
CNN	96.42	94.17	94.91	93.01
Xception	95.73	95.30	96.13	95.37
NASNetMobile	96.78	96.29	97.39	96.81
Proposed ML-GCN-LANC	**97.31**	**97.67**	**98.70**	**97.85**

From Table 2, the evaluation of various machine learning models on the diagnostic dataset of children with ASD showed accuracy in the range (88.58% to 98.70%) on the ASD children dataset. The ML-GCN-LANC model classifier with K=5 gave a maximum accuracy of 98.70%.

Table 3 – **Performance metrics of ASD Adult dataset**

Classifier	Specifi-city (%)	Sensiti-vity (%)	Accuracy (%)	F1-score (%)
Logistic Regression	85.75	86.96	86.69	86.07
SVM	85.74	88.32	88.11	87.84
CNN	90.61	89.96	91.22	90.56
Xception	91.48	92.96	93.75	92.52
NASNetMobile	96.87	96.57	97.64	98.97
Proposed ML-GCN-LANC	**98.91**	**99.10**	**99.21**	**98.41**

From Table 3, in the original database, the accuracy of several machine learning models in diagnosing ASD in adults ranged from 86.69% to 99.21%. The accuracy of the Xception model classifier at K=5 was 93.75%. In the ASD Adult dataset, ML-GCN-LANC achieved a prediction accuracy of 99.21%.

Table 4 – **Performance metrics of ASD Adolescent dataset**

Classifier	Specifi-city (%)	Sensiti-vity (%)	Accuracy (%)	F1-score (%)
Logistic Regression	84.95	84.66	85.71	84.55
SVM	86.81	87.39	88.23	87.74
CNN	89.67	89.81	90.47	89.52
Xception	90.92	91.53	92.52	91.59
NASNetMobile	95.17	95.79	96.29	95.95
Proposed ML-GCN-LANC	**97.59**	**97.35**	**98.90**	**98.12**

From Table 4, the evaluation of various machine learning models on a diagnostic dataset of adolescents with ASD showed accuracy ranging from 85.71% to 98.90% on the original dataset. The classification of the Xception model with K = 5 showed the lowest accuracy at 85.71%. The ML-GCN-LANC classifiers gave the highest prediction accuracy of 98.90% in the ASD Adolescent dataset. Fig. 6 shows the confusion scores for three deep-learning models.

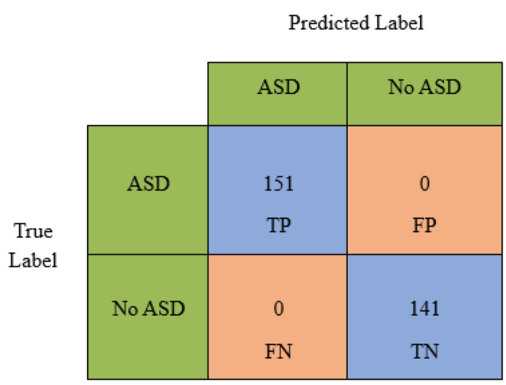


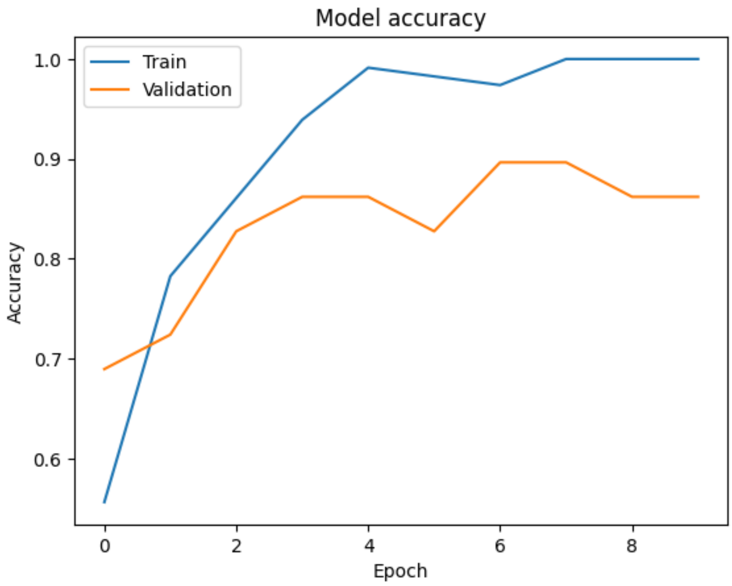
Fig. 6. Confusion Matrix of the proposed ML-GCN-LANC of ASD Adult dataset

ML-GNN achieved 99% accuracy for test data and 98% accuracy for training data. Fig. 7, a shows the accuracy characteristics. Its accuracy varies from 100% during training and from 85% to 99% during verification. ML-GCN-LANC proved to be a suitable deep-learning model for ASD detection. The loss of validation is shown as 2.0 in Fig. 7, b.

The key benefit of this method is that it is simple to apply and does not necessitate any special understanding. The proposed model achieved great accuracy (98.90%), however, accuracy can be improved because deep learning is a data-driven approach (Table 5). In comparison to earlier research that established and used a complicated computerized classification system for the diagnosis of autism spectrum disorder, the proposed method has a positive influence on the early diagnosis of autism spectrum disorder.

Table 5 – **State of art Techniques**

Authors	**Dataset**	**Accuracy (%)**
Ahmed et al. [13]	Eye-tracking data images	95.5
Zhou et al. [15]	Speech spectrogram	90
Heinsfeld et al. [18]	Autism brain imaging	70
Sewani&Kashef [19]	Autism brain imaging	84.5
Kong et al. [22]	Autism brain imaging	90.39
Haweel et al. [23]	Speech-activated brain response	81
Cilia et al. [24]	Eye-tracking data images	90
ML-GCN-LANC (proposed)	Autism brain imaging	98.90



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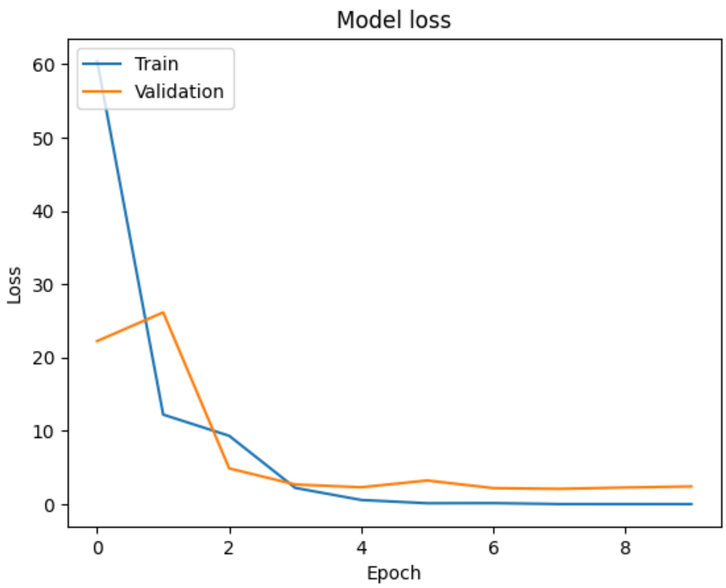

b

Fig. 7. ML-GCN-LANC performance plot:
a – Model performance; b – Model loss

Conclusions

Because medical tests are unable to detect all of the criteria for autism spectrum disorder in individuals, autism spectrum disorder assessment takes into account a variety of aspects, including unpredictable behavior, mood, structure, and psychiatric illness. Professionals employ psychological testing and feedback to identify patients with autism spectrum disorder. The testing process is hindered and made more difficult by ambiguous symptoms. There are no well-established screening procedures or improved tests that can consistently characterize autism spectrum disorder at the moment. Machine learning is the most current innovation that can save time by more accurately diagnosing autism. DL can be used to detect autism spectrum disorder in people of all ages both youngsters and adults are included. SVM was 81% accurate in detecting ASD in adults, while ML-GCN-LANC was 98% accurate. The classification of the Xception model with K = 5 showed the lowest accuracy at 92.52%. The ML-GCN-LANC classifiers gave the highest prediction accuracy of 98.90% in the adolescent ASD dataset. Several transfer learning models, like as MobileNet and ResNet, could be used to detect ASD using image datasets from autistic children in the future. Future deep learning algorithms can also be used to identify the level of disability.

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Нове виявлення розладів спектру аутизму за допомогою мультиміткової графової згорткової мережі із згорткою сусідніх міток уваги

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Анотація. Через відсутність точних медичних тестів на аутизм, таких як аналізи крові для виявлення захворювання, діагностика розладу спектру аутизму (РАС) виявилася складною. Поширеність обмежувальної та/або повторюваної поведінки, а також труднощі та порушення соціального спілкування є характерними ознаками розладів аутистичного спектру. Цей поведінковий стан було виявлено. Лікарі оцінюють історію розвитку та поведінку дитини, щоб поставити діагноз. **Результати дослідження.** У цьому дослідженні використовувалася гібридна згортка з кількома мітками-графами (ML-GCN) із згорткою околу, що звертає увагу на мітки, щоб класифікувати розлад спектру аутизму. Він пропонує чіткий і ефективний модуль обгортки графа, зокрема для збору даних локальних атрибутів конкретного вузла для створення логічного представлення функціонування вузла. Крім того, гомеопатична теорія рекомендує розробити таксономію термінів, пов'язаних з увагою. Крім того, розроблено техніку адаптивного графа, яка дозволяє моделі вивчати ядро для кожного рівня динамічно та унікально, дозволяючи моделі отримати більш цінні та ефективні функції. На трьох часто використовуваних еталонних наборах даних, включаючи налаштовані та неспеціалізовані мережі, було проведено комплексні тести для перевірки підходу до класифікації за кількома мітками на основі нейронної мережі.

Ключові слова: розлад спектру аутизму; графова згортка; згортка сусідніх меток уваги; точність; інформаційна система підтримки прийняття рішень.