Image Analysis using Classification Method for Autism Spectrum Disorder

[1]Sudharani, [2]Nethravathi B

[1,2]M.Tech in Data Science, Department of Information Science and Engineering, JSS Academy of Technical Education, Bengaluru, Karnataka, India

[1]nethravathi.sai@gmail.com, [2]sudharani7887@gmail.com

Abstract: The growing need for accurate and efficient classification systems has led to the integration of ML algorithms and DL into different areas. This work uses structured CSV data with unstructured image data to create a hybrid classification framework that improves the overall accuracy and durability of classification models. Pre -processing processes for a structured data file include deprivation of duplicate attributes and coding labels. Ten ML techniques are used: decision-making classifier, random forest regressor, linear discriminatory analysis, vector "Support Vector Classifier (SVC), Gradient Boost, Logistic Regression, Gaussian Naive Bayes, K-Nearest Neighbors (KNN)" The image data generator is used for preliminary processing of unstructured image data by changing, zooming, editing, overturning and transformation. A "convolutional neural network (CNN)" is used to select functions and sorting processed images. "To see how well the model works, the used measurement measures include accuracy, download and F1-skore. The XGBOOST classifier has the highest accuracy of 94.27%on tabular data, while the CNN has 96.85%accuracy" on the image data file. This shows that the CNN model is better when classifying images.

"Index Terms - *Machine learning, deep learning, classification, CNN, XGBoost, preprocessing, image augmentation, accuracy".*

1. INTRODUCTION

Digital technologies are growing at exponential pace, which caused an unprecedented increase in the amount of data created in many areas such as health, banking, education and social media. Because of this huge amount of data organized and unstructured, there is an urgent need for intelligent systems that can quickly and efficiently process, analyze and classify data. It is very important to be able to get useful information from such large data sets so that people can make intelligent decisions, especially in sensitive areas such as health care and behavior diagnostics [1]. "Autism Spectrum Disorder (ASD)" is a complicated neurodevelopmental disorder that has become a very important area of research for successful intervention and support from early and accurate diagnosis. Conventional diagnosis techniques are laborious, subjective and require trained specialists and therefore underline the importance of automated, intelligent diagnostic systems [2]. [3].

Recent progress in ML and artificial intelligence has changed the way we sort and find patterns in data. Access to ML, especially approaches used on structured table data, showed promising in search of patterns associated with behavior problems [4]. At the same time, DL models, in particular the convolutional neural network (CNN), have changed the way the images are classified, allowing small visual stimuli associated with ASD in facial images [5] [6]. These approaches provide an objective, more scalable and efficient approach to diagnostic classification and increase the opportunity for early intervention and monitoring [7].

Many research has been carried out on how to integrate the properties of the face, water tracks and structured data sets to create reliable classification algorithms of ASD [8]. Scientists were able to create models that work well in real situations thanks to better computers and access to high quality information [9]. This project seeks to strengthen the growing landscape by developing an intelligent classification system that uses both CSV structured data and unstructured image data to increase diagnostic accuracy in autism applications.

2. RELATED WORK

Numerous studies examined the use of artificial intelligence methodologies and ML to identify and categorize the "Autism Spectrum Disorder (ASD)", underlining the potential of these technologies to increase diagnostic efficiency and accuracy. Health care has seen an exponential increase in structured and unstructured data, which caused it to create intelligent diagnostic tools that can manage well and analyze complicated data. In this respect, ML methods for structured data sets and DL models for image -based categorization have become very popular in ASD research.

One of the areas of study was the use of structured table data, including answers to surveys and demographic information, to create predictive models. These models often use subordinate teaching techniques such as "Support Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Decision Trees (DT)", which showed significant efficiency in the detection of behavioral patterns associated with ASD. The advantage of using these types of models is that they are easy to understand and can handle categorical features well. Scientists have found that the integration of the selection techniques with these classifiers can improve the predicted accuracy by removing redundant or irrelevant input elements [10]. File approaches such as voting classifiers and techniques of increasing strengthening have been implemented to consolidate the judgments of several models and therefore increase the resistance of ASD detection systems [11].

Along with structured data, another important area of research is the use of DL methods on unstructured image data, especially facial images. These models are made to find small marks and expressions that are usually associated with ASD. "Convolutional neural networks (CNN)" were very good in classification of images for ASD diagnosis because they can extract functions hierarchically. CNN - based architecture can automatically learn to distinguish functions from facial photos, eliminating the need for manual engineering functions, making it exceptionally ideal for real -time applications [12].

Das et al. [13] They released a hybrid architecture that connects CNNS with file approaches to improve ASD detection from face images. Their approach used both learning and fusion at the level of decision -making, which will improve things than models that worked on their own. The study emphasized the efficiency of hybrid structures in identifying nuancement formulas that one model systems cannot detect. Another study also dealt with how to combine image and spreadsheet data using multimodal fusion methodologies. This has led to more complete diagnostic frameworks that use visual and behavioral tracks [14].

Numerous studies emphasized the importance of the elements extraction strategies. For example, facial landmarks, geometric ratios and segmentation techniques based on the region were used to preliminary processing of image data before entering DL models. These methods allow the model to pay more attention to important parts of the face, such as eyes, lips and jaws that are commonly associated with emotional manifestation and eye contact behavior - two important features in the asd rating [15]. Scientists have shown that models trained with focused functions can significantly overcome models trained in raw images, especially in solving limited data sets [16].

Transmission learning has also become a common method in researching ASD classification to solve the problem that it does not have enough data. Scientists were able to fine -tune high -performance architecture for ASD detection tasks with relatively limited data sets using pre -trained CNN models such as VGGNET, Resnet and Inception. This method not only shortens to the time of training, but also uses the rich representation of functions obtained from the huge data sets of image, which makes models more generalizable [17].

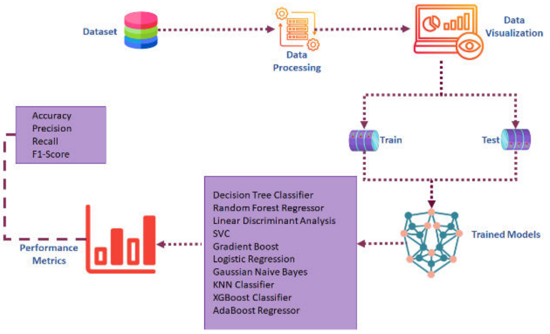
Recent development includes the implementation of attention mechanisms and explained AI methodology to improve the transparency of DL models. These increments help practices and doctors to find out which parts of the image or functions had the greatest impact on the final judgment. As a result, people trust automated systems [18]. These types of models are suitable for the target to create diagnostic tools that are easily understandable, reliable and focused on users that can be used in a clinical environment.

In addition, research emphasized the importance of data file quality, accuracy of annotation and demographic diversity in creating effective ASD detection systems. Classification models can be very unfair and do not work well, if class distribution is not balanced, labels are noisy or data are not representative. To solve these problems, scientists looked at methods, including data augmentation, resampling and employing a "GAN (generative contradictory network)" to create false data [19]. The aim of these strategies is to improve model training by providing data sets that are more balanced and richer, which better shows heterogeneity in ASD presentations.

In conclusion, literature strongly supports the use of ML and DL to create intelligent ASD finding systems. The use of structured table data makes it easier and clearly modeling behavioral features and, using DL in the images on the face, selects non - verbal tracks that are important for autism diagnosis. Hybrid techniques, multimodal fusion, transmission learning and explained AI are important new ideas that have worked together to make these systems work better and more likely to be used. As research increases, the creation of more general, interpreted and ethically healthy models is essential for the effective use of AI -based solutions in practical ASD diagnostic contexts [20].

3. MATERIALS AND METHODS

The proposed approach wants to use the techniques of deep learning and a hybrid file to develop a strong classification model to find bone fractures and long -term illnesses. To extract spatial characteristics from radiography images in the data set of bone images in the bone fracture data set, the architecture of the "Convolutional Neural Network (CNN)" is used. There are layers such as convolution, activation of REL, maximum association, flattening and dense layers. ImageDatagenerator is used to provide new data in real time to help the model better generalize [12]. During the training, early stop layers and premature ending of school attendance are added to prevent excessive acceptance. A file learning model is designed to predict chronic diseases using plate data. This model combines a "decision tree, a random forest, K-Nearest Neighbors (KNN)" and Catboost classifiers in a soft vote system to improve accuracy and deal with non-linearity and function interactions [18]. During preliminary processing, the selection of functions and correlation filtering is used to remove unnecessary columns. This ensures that the model is practicing quickly [14]. This strategy with two spikes improves the accuracy of predictions in a wide range of data.



"Fig. 1. Proposed Architecture – CSV Dataset"

Fig 1 shows the proposed structure of the ML pipe. The procedure begins with the CSV data file, which is then processed and visualized. Then the data is divided into two groups: Train and Test. Algorithms, such as a tree classifier, create various trained models. Finally, the models are tested using metrics, including accuracy, accuracy, memories and score F1.

"Fig. 2. Proposed Architecture – Image Dataset"

Fig. 2 It shows the proposed structure for classification of images. First, the data set of images is processed and sent to a "convolutional neural network (CNN)". CNN uses a convolutional and sub -layer to process images and find functions. The result is a fully connected layer that creates trained models. Then the power measurement is used to see how well these models work, which completes the ML process.

i) Dataset Collection:

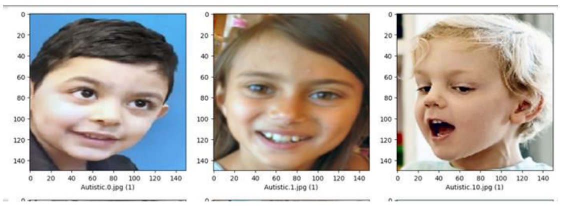
CSV Dataset: The structured data file used in this work was obtained in CSV format from trusted open source storage and includes 1,054 items with 18 attributes related to "autism spectrum disorders (ASD)". There is a separate line for each event, including information such as age, gender, ethnicity, family history and behavioral brands. The target class shows whether there are ASD features, allowing categorization under supervision. For the first time we used pandas to inspect the data file and checked its properties [18]. FIG. 3 shows an overview of the structure and content of the CSV data file.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	Age_Mons	Qchat-10-Score	Sex	Ethnicity	Jaundice	Family_mem_with_ASD	Who completed the test	Class/ASD Traits
0	0	0	0	0	0	0	1	1	0	1	28	3	f	middle eastern	yes	no	family member	No
1	1	1	0	0	0	1	1	0	0	0	36	4	m	White European	yes	no	family member	Yes
2	1	0	0	0	0	0	1	1	0	1	36	4	m	middle eastern	yes	no	family member	Yes
3	1	1	1	1	1	1	1	1	1	1	24	10	m	Hispanic	no	no	family member	Yes
4	1	1	0	1	1	1	1	1	1	1	20	9	f	White European	no	yes	family member	Yes
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1049	0	0	0	0	0	0	0	0	0	1	24	1	f	White European	no	yes	family member	No
1050	0	0	1	1	1	0	1	0	1	0	12	5	m	black	yes	no	family member	Yes
1051	1	0	1	1	1	1	1	1	1	1	18	9	m	middle eastern	yes	no	family member	Yes
1052	1	0	0	0	0	0	0	1	0	1	19	3	m	White European	no	yes	family member	No
1053	1	1	0	0	1	1	0	1	1	0	24	6	m	asian	yes	yes	family member	Yes

1054 rows × 18 columns

“Fig. 3. CSV Dataset”

Image Dataset: The study uses a publicly accessible data set of images consisting of facial photographs organized in established categories for categorization purposes. Photos are stored in files for each lesson and have different lighting, background and orientations that help CNN generalization. Tensorflow and Keras are used for preliminary data file processing and all images are reduced to be used as an input for the model. This organized method ensures that learning from information at the pixel level is done quickly and well [1]. Figure 4 provides several sampling photos from the data file that shows how data is organized on the label and how it changes.



“Fig. 4. Image Dataset”

ii) Pre-Processing:

Pre-processing is a critical step in ML and DL pipelines, ensuring that data is clean, consistent, and optimized for model training. For this study, both structured (CSV) and unstructured (image) datasets underwent rigorous pre-processing tailored to their formats. This enhances model performance, reduces overfitting, and improves generalization on unseen data [1].

1. CSV Dataset Pre-processing: Pre -processing is an important part of the pipe for machine learning and deep learning, because it ensures that the data is clean, consistent and ready to train the model. For this examination, both structured (CSV) and unstructured (image) data sets of extensive preliminary processing adapted to their formats. This makes the model better, prevents overfilling and improves new data [1]. To prepare data for classification models, it includes preliminary processing of CSV data file Cleaning, encoding and visualization of data. To begin with, tools like pandas are used to remove columns that are not needed or are too similar, as these types of functions can add noise and reduce the model. To make the data file easier to work, columns with constant values or IDs that do not help to make predictions are omitted. [2] Then we use Labencoder () from Scikit-Learn to transform categorical characteristics such as "sex", "jaundice" and "family_MEM_WITH_ASD" to numbers. This phase ensures that all data can read machines and make the model more compatible. Histograms, boxPlots and correlation thermal maps are examples of visualization that can be used to find outlying values, look at the distribution of functions and check the class imbalance. Before training, libraries such as SEABORN and MATPLOTLIB are used to look at data quality. These visual knowledge allows you to select which features to be included and how to normalize them, ensuring that the pipeline is strong. In general, these preparation techniques make it more reliable and helping to categorize better.

2. Image Dataset Pre-processing: Preliminary processing of data set of images is ready for facial images for classification based on CNN. This begins with a change in change, which means the division of pixels by 255 to get to the range of 0 to 1. This step makes it easier to converge and keep the numbers stable during training. Shear transformation causes geometric aberrations that help the model learn from different aspects. Zoom is more resistant to changes in the Simulation of Changes at the distance of the subject in the real world. Horizontal overturning adds to data by looking the same on both sides, which helps functions to learn CNN that does not depend on orientation. This is particularly useful for facial data sets. To avoid excessive filling, Keras uses the ImageDatagenerator to apply all augmentations during the training phase. [3] Reshapping also ensures that all photos fit in the predetermined input size (as 128 × 128), which maintains a data file consistent and most uses the GPU RAM. These pre -processing methods help the model find useful properties in different situations, which is a more accurate classification.

iii) Training & Testing:

CSV and image data sets are divided into training and test kits with a ratio of 80:20 to ensure that the classification is strong. This allows the model to learn from a wide range of data while being trained and checks that it can generalize to new samples when it is tested. Augmentation is performed before the image data is separated. This method helps to avoid overfilling and ensures that tasks are always evaluated in the same way. It ensures that the model works not only during training, but also when used in the real world, which is more reliable [15].

iv) Algorithms:

1. Decision Tree Classifier (CSV Dataset): The tree classifier divides the data into branches based on the function values. It does this by using rules such as the Gini index or the profit of information. It can work with numbers and categories with little work, so it works well with organized data sets. If the trimming does not apply, excessive problems may become, although it is easy to understand and fast. In the CSV data files, it explains the decision to gain quick knowledge and find out how you are doing [13].

2. Random Forest Regressor (CSV Dataset): A random regressor Forest is a group of decision - making trees that have been trained on random data subsets (bagging). It is more durable and less likely to translate than one tree. It is usually used for regression, although it works well for classification. It works well with structured data sets such as CSV, where there are many features that interact with complicated ways [16].

3. Linear Discriminant Analysis (CSV Dataset): LDA is a subordinate method for classification and reduction of dimensions that projects data to make the classes as much as possible. This is best for data sets that can be separated by a line because it assumes that classes are usually distributed with the same deviations. LDA improves classification in structured CSV data sets by facilitating high size input space, reducing noise and allowing models when there is a problem with multicollinearity [18].

4. Support Vector Classifier (CSV Dataset): SVC creates hyperplane, which makes the range between classes as wide as possible. It uses cores such as RBF, to change the entry to a higher dimensional space, unless the data is linear. It works well with high -dimensional data and does not overcome well in control. When used on CSV data sets, it creates accurate, generalizable boundaries between classes, but it can be difficult on computers [17].

5. Gradient Boost (CSV Dataset): Increasing the gradient makes models by a second and each fixes errors before using a gradient descent. He uses weak students who are usually decision -making trees to reduce bias and improve predictions. It works well on structured data because it is possible to change the level of learning and loss. It works well with data sets that require high accuracy, such structured CSV, but careful calibration to prevent overfill [12].

6. Logistic Regression (CSV Dataset): Logistic regression uses a sigmoid function to convert input characteristics into binary or more class outputs and then predicts probability. It is fast and easy to understand, which is great for organized data that can be separated by a line. Regularization (L1/L2) stops excessive and therefore it is a good baseline. It works well with CSV data sets that have simple and clear rules, especially when correlations between functions and linear targets [11].

7. Gaussian Naive Bayes (CSV Dataset): Naive Gaussian Bayes uses Bayes' sentence that assumes that functions are independent and inputs are regularly distributed. It is fast and works well, especially for organized data sets with many dimensions. Although the assumption of independence may not always be true, it usually provides good basic results, especially if the data is clean, CSV marked with well distributed numerical features [15].

8. K-Nearest Neighbor Classifier (CSV Dataset): KNN sorts things by finding the closest training samples to and using a distance such as Euclidean to find out which one is closest. It does not need the phase of training, but it costs a lot of money on the forecast. KNN is best for small and clean data sets because it can find non -linear decision -making limits. In CSV data sets, this works well when the class boundaries are not straight and the elements are scalped correctly [11].

9. XGBoost Classifier (CSV Dataset): XGBOOST improves the increase in gradient by adding regularization, parallelization and ability to solve the missing values. They build trees one by one and make sure they are as quickly and accurate as possible. XGBOOST works well with structured data because it has good prediction performance and can be trained on a large scale. It is the best choice for competitive ML situations because it is so flexible [16].

10. AdaBoost Regressor (CSV Dataset): Adaboost regressor increases weak students with iteration weight adjustment and focuses on incorrectly classified examples. It creates final predictions by averaging with weights. It works well to improve accuracy on clean organized files such as CSV, but is sensitive to noise. It reduces distortion and scattering, which makes models with temporary individual accuracy better [16].

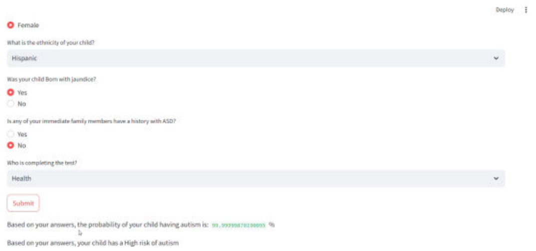
11. CNN (Image Dataset): The deep teaching models called a “convolutional neural network (CNN)” learn the spatial hierarchy from the pictures. In layers there are convolutional filters, association and dense layers. The last layer is Softmax, which is used for classification. Inverting, enlargement and cut are examples of data augmentation techniques that help generalize. When CNN is used on the image data file, it automatically finds features that make the image classification accurate and strong [14].

4. RESULTS AND DISCUSSIONS

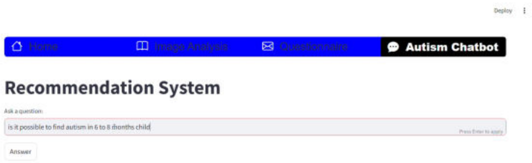
“Fig. 5. Image Analysis Upload Input Image”

“Fig. 6. Output”

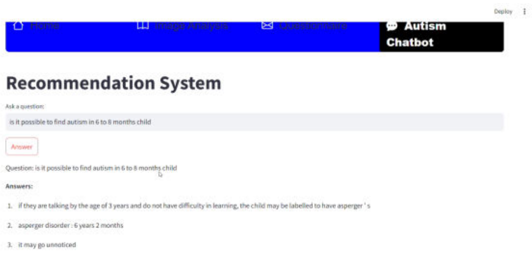
“Fig. 7. Upload Questionnaire”



“Fig. 8. Output for Upload Questionnaire”



“Fig. 9. Chatbot Question”



“Fig. 10. Output”

5. CONCLUSION

The study shows that a hybrid categorization frame that combines structured and unstructured data can increase prediction accuracy. The system effectively captures complex formulas and correlations in various data sources by methodical processing of spreadsheet and visual information through different workflows. For structured CSV data, preliminary processing methods, such as the reduction of attributes and label coding, the input for training the model clean and easy to understand. The XGBOOST classifier routinely beats other machine learning models, with a rate of accuracy of 94.27%, which shows that it can handle complicated interactions of the elements and prevent excessive connection. The pipeline for augmentation of the whole picture, which includes techniques such as zooming, change and overturning, improves the diversity of training set for unstructured image data, helping to generalize the model better. “The convolutional neural network (CNN) used to categorize images works better than other methods, gaining an accuracy of 96.85%”. These results show that the hybrid classification system is strong and works well, which shows that it could be used for scalable and accurate classification in the real world, where both structured records and visual inputs are used.

Future works include the inclusion of automated hyperparameters tuning methods such as Bayesian optimization, facilitating real -time deployment over edge devices and using multimodal merger data in conjunction with DL techniques. Adding complex models such as transformers and vision transformers could improve learning functions. Explainable AI (XAI) methods will be clearer and transmission learning will help things work in different areas. Continuous teaching framework may make sure that the models are updated without having to retrain from zero. As a result, they are more robust and able to handle a wider range of categorization jobs in real situations.

REFERENCES

[1] Atlam, E. S., Aljuhani, K. O., Gad, I., Abdelrahim, E. M., Atwa, A. E. M., & Ahmed, A. (2025). Automated identification of autism spectrum

disorder from facial images using explainable deep learning models. *Scientific Reports*, *15*(1), 26682.

[2] Kumar, A., & Jaiswal, U. C. (2025). Predicting Autism Spectrum Disorder in Adults Through Facial Image Analysis: A Multi-CNN with BiLSTM Model. *SN Computer Science*, *6*(3), 254.

[3] Contreras, R. C., Viana, M. S., Bernardino, V. J. S., Santos, F. L. D., Toygar, Ö., & Guido, R. C. (2025). A multi-filter deep transfer learning framework for image-based autism spectrum disorder detection. *Scientific Reports*, *15*(1), 14253.

[4] Ibadi, H., & Lakizadeh, A. (2025). ASDvit: Enhancing autism spectrum disorder classification using vision transformer models based on static features of facial images. *Intelligence-Based Medicine*, *11*, 100226.

[5] Farhat, T., Akram, S., Rashid, M., Jaffar, A., Bhatti, S. M., & Iqbal, M. A. (2025). A deep learning-based ensemble for autism spectrum disorder diagnosis using facial images. *PLoS One*, *20*(4), e0321697.

[6] Herath, L., Meedeniya, D., Marasinghe, J., Weerasinghe, V., & Tan, T. (2025). Autism spectrum disorder identification using multi-model deep ensemble classifier with transfer learning. *Expert Systems*, *42*(2), e13623.

[7] Sabeeh, S. (2025). Comparative Deep Learning–Based Facial Image Analysis for Early Autism Prediction in School-Aged Children. *Misan Journal of Engineering Sciences*, *4*(1), 123-141.

[8] Manoj, G., Gupta, V., Bhattacharya, A., Aleem, S. G. A., Vedantham, D., A, A. P., & Agastinose Ronickom, J. F. (2025). Diagnostic classification of autism spectrum disorder using sMRI improves with the morphological distance-related features compared to morphological features. *Multimedia Tools and Applications*, *84*(8), 4979-5000.

[9] Altomi, Z. A., Alsakar, Y. M., El-Gayar, M. M., Elmogy, M., & Fouda, Y. M. (2025). Autism Spectrum Disorder Diagnosis Based on Attentional Feature Fusion Using NasNetMobile and DeiT Networks. *Electronics*, *14*(9), 1822.

[10] Parvathy, R., Arunachalam, R., Damodaran, S., Al-Razgan, M., & Ali, Y. A. (2025). An intellectual autism spectrum disorder classification framework in healthcare industry using ViT-based adaptive deep learning model. *Biomedical Signal Processing and Control*, *106*, 107737.

[11] Manjunath, K. M., & Veeramani, V. (2025). A novel thermal imaging-based framework for continuous ASD classification and behavior analysis using facial mood and skin temperature features. *Biomedical Signal Processing and Control*, *100*, 107009.

[12] Ahmadiar, A., Melinda, M., Muthiah, Z., Zainal, Z., & Rizky, M. M. (2025). Thermal Image Classification of Autistic Children Using Res-Net Architecture. *Indonesian Journal of Electronics, Electromedical Engineering, and Medical Informatics*, *7*(1), 1-10.

[13] Alam, M. S., Rashid, M. M., Jazlan, A., Alahi, M. E. E., Kchaou, M., & Alharthi, K. A. B. (2025). Robust Autism Spectrum Disorder Screening Based on Facial Images (For Disability Diagnosis): A Domain-Adaptive Deep Ensemble Approach. *Diagnostics*, *15*(13), 1601.

[14] Werdiningsih, I., Puspitasari, I., & Hendradi, R. (2025). Recognizing daily activities of children with autism spectrum disorder using convolutional neural network based on image enhancement. *Cybernetics and Information Technologies*, *25*(1).

[15] Khan, K., & Katarya, R. (2025). S/SD-ASD: Self-supervised and self-distillation learning approach for classifying autism spectrum disorder in children using facial images. *Engineering Analysis with Boundary Elements*, *179*, 106382.

[16] Al-Nefaie, A. H., Aldhyani, T. H., Ahmad, S., & Alzahrani, E. M. (2025). Application of artificial intelligence in modern healthcare for diagnosis of autism spectrum disorder. *Frontiers in Medicine*, *12*, 1569464.

[17] Kang, L., Chen, M., Huang, J., & Xu, J. (2025). Identifying autism spectrum disorder based on machine learning for multi-site fMRI. *Journal of Neuroscience Methods*, *416*, 110379.

[18] Rajkumar, S. C., Cirillo, S., Yuvasinsi, D., & Solimando, L. (2025). A hybrid approach combining images and questionnaires for early detection and severity assessment of Autism Spectrum Disorder. *Image and Vision Computing*, 105547.

[19] Ghnemat, R., Al-Madi, N., & Awad, M. (2025). An intelligent approach for autism spectrum disorder diagnosis and rehabilitation features identification. *Neural Computing and Applications*, *37*(4), 2557-2580.

[20] Das, A., Pattnaik, P. K., & Bandyopadhyay, A. (2025, February). Early Intervention in Autism Spectrum Disorder: Hybridizing Convolutional Neural Networks with Ensemble Methods for Enhanced Detection Using Facial Imagery. In *2025 3rd International Conference on Intelligent Systems, Advanced Computing and Communication (ISACC)* (pp. 781-786). IEEE.