Milestone Transactions on
MEDICAL TECHNOMETRICS
Vol. 03 | Issue. 02 | 2025

RESEARCH ARTICLE OPEN ACCESS

Early Detection of Autism Spectrum Disorder using Transfer Learning on Brain Imaging Data

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DOI: **10.5281/zenodo.15267784**
Received: 22 February 2025 / Revised: 27 March 2025 / Accepted: 30 March 2025

Abstract - This study focuses on classifying and representing learning tasks using powerful deep learning models, including Convolutional Neural Networks (CNN) and Transfer Learning algorithms. The analysis utilizes data from the Autism Brain Imaging Data Exchange (ABIDE I and ABIDE II) datasets. It explores the application of deep learning techniques to enhance the detection of Autism Spectrum Disorder (ASD). Functional magnetic resonance imaging (fMRI) data has shown potential in identifying brain irregularities associated with ASD. We utilize Convolutional Neural Networks (CNNs) combined with transfer learning to analyse fMRI data from the Autism Brain Imaging Data Exchange (ABIDE) dataset. Our optimized CNN model achieves an accuracy of 81%, surpassing conventional classification models. This research establishes deep learning as a promising tool for ASD diagnosis, evaluated based on accuracy, precision, and recall.

Index Terms – Autism Spectrum Disorder(ASD), Deep Learning, Convolutional Neural Networks (CNNs), Transfer Learning, fMRI, Image Processing.

I. INTRODUCTION

The complex neurological and developmental disorder known as autism spectrum disorder (ASD) affects a person's capacity for social interaction, communication, learning, and behaviour. The reason it is classified as a "developmental disorder" is that the symptoms usually appear during the first two years of infant life. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5) states that people with ASD frequently struggle with social communication and interaction, have limited interests, and engage in repetitive behaviours that can interfere with many facets of everyday living. The word "spectrum" describes how widely symptoms and intensity vary from person to person. People of various backgrounds,

Electronic ISSN: **2584-072X**

irrespective of gender, ethnicity, or socioeconomic level, can be impacted by ASD. Even though it is a chronic illness, symptoms can be improved and everyday functioning can be improved with early intervention and specialised assistance. All children should undergo routine autism screening, according to the American Academy of Paediatrics, and parents are urged to speak with medical specialists regarding ASD assessments.

Our optimised Convolutional Neural Network (CNN) outperformed earlier classification techniques in this study, achieving an 81% accuracy rate in differentiating between autistic and normally growing brains. This study demonstrates how deep learning may be a useful diagnostic tool for ASD. We examine important measures like accuracy, precision, and recall in order to evaluate the model's performance in more detail. Image processing, which includes a variety of methods to improve photos or extract useful information, is essential to the analysis of visual data. It belongs to the more general category of signal processing, in which an image is the input and an image, certain features, or extracted data may be the output. Image processing is a rapidly developing topic that is extensively studied in computer science and engineering.

There are two primary categories of image processing:

1. Analog : Analog image processing is used for physical formats like printed images and photographs, where analysts rely on interpretative methods.
2. Digital : Digital image processing, on the other hand, involves the manipulation of digital images using computational technique in image processing.

This process typically consists of three key stages:

i. Preprocessing
ii. Augmentation
iii. Information extraction.

Applications for digital image processing are numerous and include computer vision, remote sensing, medical imaging, and multimedia. In order to accurately distinguish between brain patterns associated with autism and those that are not, this study focusses on processing fMRI data using CNNs and transfer learning.

II. LITERATURE SURVEY

Predicting brain age from Magnetic Resonance Imaging (MRI) has significant potential for the early detection of neurological disorders. This study examines the effectiveness of Convolutional Capsule Networks (ConvCaps) in classifying brain age using MRI scans. ConvCaps, a relatively new deep learning architecture, aim to overcome certain limitations of traditional Convolutional Neural Networks (CNNs), such as their inability to maintain spatial relationships and their tendency to overfit data. To evaluate performance, we compared ConvCaps with established deep learning models like InceptionV3 and DenseNet, utilizing the OASIS dataset, which consists of 436 brain MRI scans. While ConvCaps demonstrated an accuracy of 81%, InceptionV3 performed slightly better, achieving 85% accuracy. Both models showed promise in brain age classification, indicating their potential use in this field. Future research could focus on fine-tuning hyperparameters and integrating ConvCaps with other architectures to enhance performance. This study highlights the growing role of deep learning in leveraging MRI analysis for the early diagnosis of neurological disorders.

Deep Learning for ASD Classification from rs-fMRI Data

A separate study focuses on using deep learning to classify Autism Spectrum Disorder (ASD) based on resting-state functional MRI (rs-fMRI) data. The high-dimensional nature of rs-fMRI (four-dimensional data) presents a challenge for deep learning models. To address this, the researchers employed temporal transformations to summarize time-based information before training a 3D Convolutional Neural Network (3D-CNN). Results showed that the 3D-CNN achieved a classification accuracy of approximately 66% on a combined dataset. However, its performance was similar to that of a Support Vector Machine (SVM), indicating that the applied transformations may not have added significant predictive value. This suggests that future research should explore alternative representations of temporal information in rs-fMRI data to improve deep learning models for ASD classification.

III. METHODS & MATERIALS

This section provides an overview of the ABIDE datasets and the classifiers used in this study. It also explores various applications discussed by different researchers. Additionally, performance indicators are assessed based on factors such as available resources, early diagnosis, and overall model effectiveness. These evaluation criteria are applied uniformly across all data. Finally, the section concludes with a detailed explanation of the proposed research methodology, including comprehensive diagrams for better understanding.

A. Dataset Description

This study utilizes data from the Autism Brain Imaging Data Exchange (ABIDE) to build a dataset for further analysis. The ABIDE dataset has been widely used by researchers to classify individuals with Autism Spectrum Disorder (ASD) and typically developing controls based on MRI scans. ABIDE-I comprises 1,112 resting-state functional MRI (rs-fMRI) datasets, including 539 individuals with ASD and 573 typically developing individuals. ABIDE-II expands on this, consisting of 1,014 rs-fMRI datasets, with 521 ASD subjects and 593 typical controls. Data for both datasets were collected from 17 different research sites.

ABIDE-I was the initial release, gathering imaging, anatomical, and phenotypic data from 17 international sites to facilitate research collaboration. This dataset, released in August 2012, includes individuals aged 7 to 64 years, with a median age of 14.7 years. To enhance research into the neurological basis of ASD, ABIDE-II was introduced, adding over 1,000 datasets with more detailed phenotypic information. It also includes longitudinal samples from 38 individuals collected over 1 to 4 years. ABIDE-II now consists of data from 19 contributing institutions, with 1,114 datasets, including 521 ASD cases and 593 control participants.

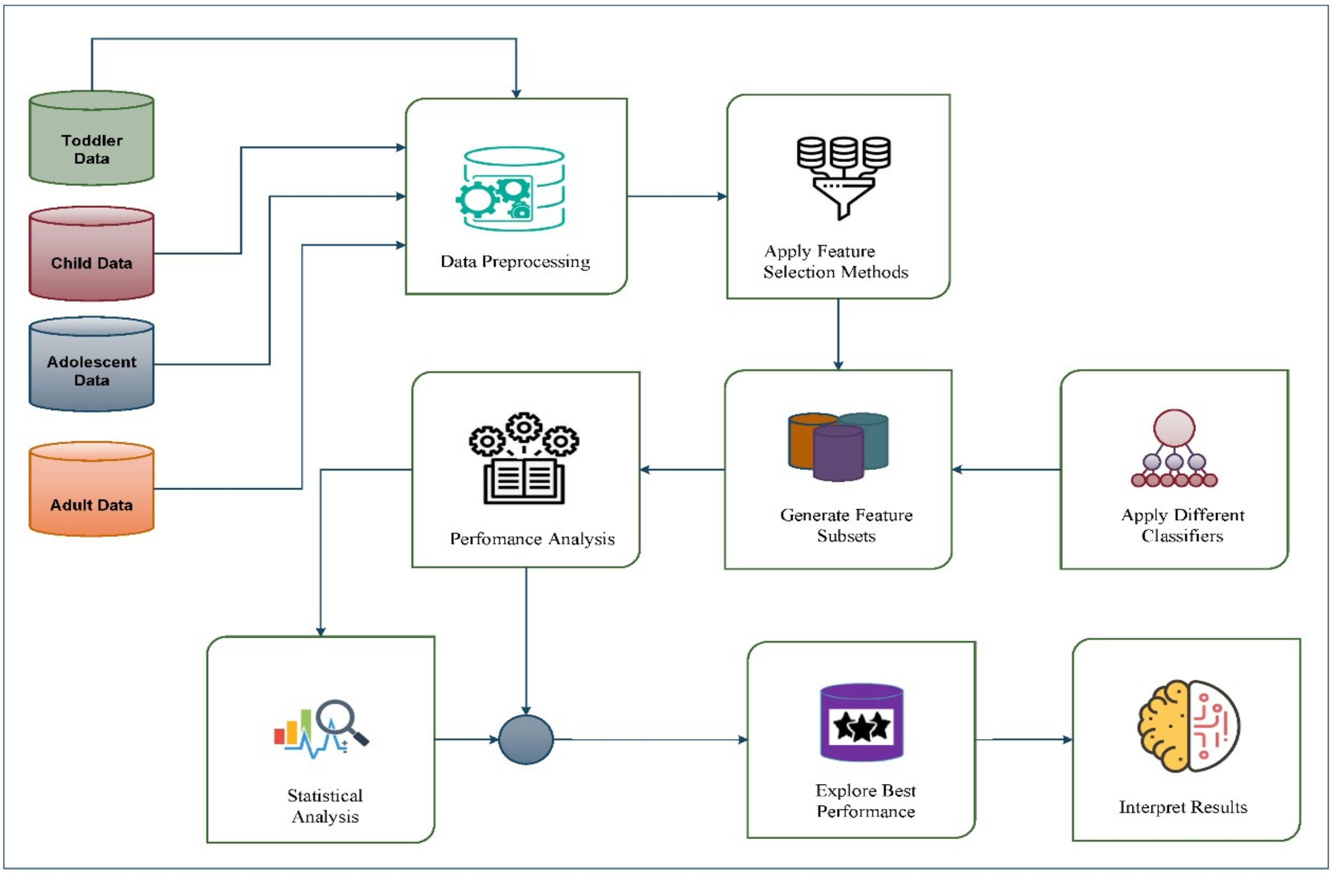
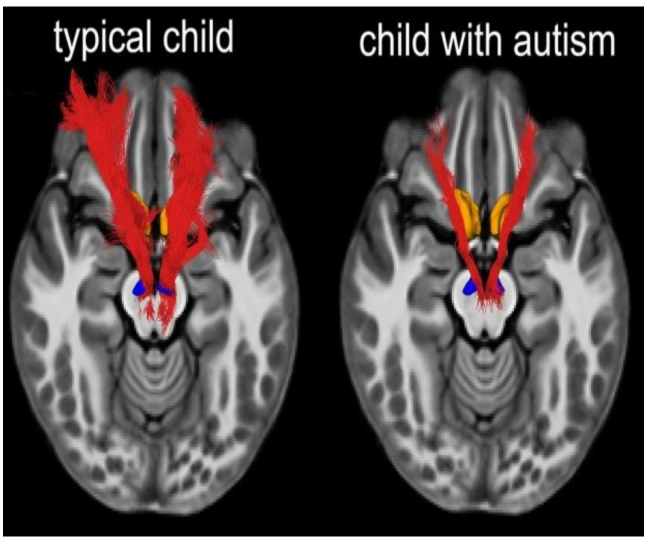
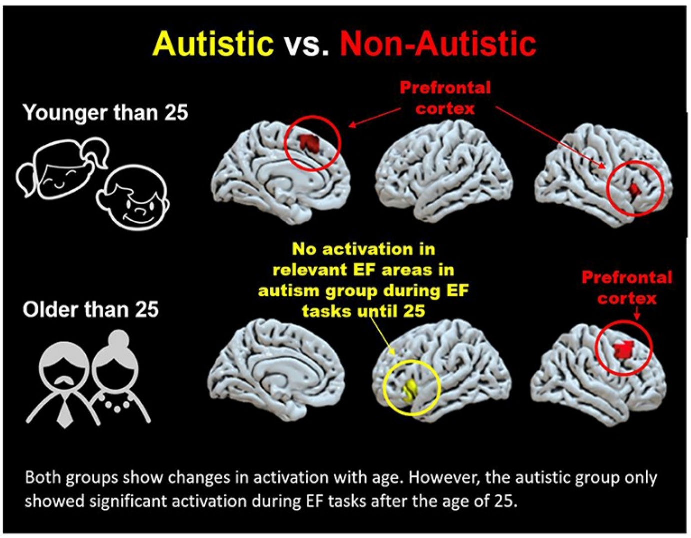


Fig. 1: Dataset preparation

The above figure represents a data processing and analysis pipeline. It starts with different datasets (Toddler, Child, Adolescent, and Adult data) undergoing Data Preprocessing. Feature selection methods are applied, followed by generating feature subsets and applying different classifiers. Performance analysis and statistical analysis help explore the best-performing models. Finally, results are interpreted for insights and decision-making.





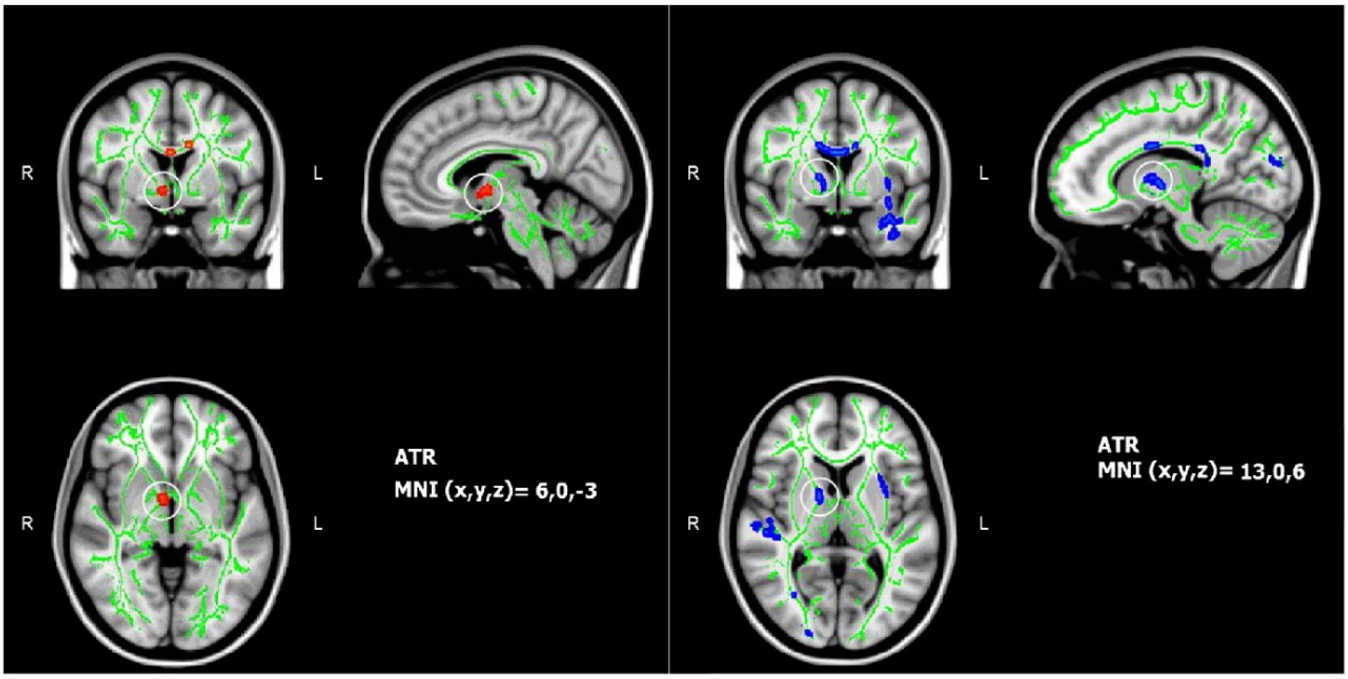


Fig. 2: Sample Data

B. Classifier

A classifier is a function or hypothesis used to assign specific labels to instances within a dataset based on predefined parameters. It categorizes data by analysing key features and grouping them accordingly. The following classifiers have been utilized in this research. In recent years, Convolutional Neural Networks (CNNs) have gained prominence in medical data analysis, including lesion segmentation, anatomical segmentation, and classification. CNNs assign weights to image features, distinguishing different patterns effectively. Compared to traditional classification techniques, CNNs require less preprocessing and can automatically learn important filters and characteristics during training. By using filters, CNNs capture spatial and temporal relationships in images. The architecture is designed to optimize performance by reusing weights and reducing the number of parameters, making it highly adaptable to image datasets.

Transfer learning is another approach that enhances model accuracy while requiring less training time and data. Instead of starting from scratch, transfer learning leverages pre-existing patterns from models trained on large datasets. These pre-trained models serve as a foundation, allowing the model to refine its learning on a new, smaller dataset with improved efficiency. As a result, transfer learning enables faster training while maintaining high precision in classification tasks.

C. Proposed Methodology

A research methodology consists of systematic procedures designed to address a specific problem. This section outlines the methods employed in this study, detailing each step involved in the research process. The proposed approach includes an algorithm capable of classifying datasets into two categories and making predictions accordingly. The entire study was structured into six phases, starting from data collection and concluding with data classification for predictive modeling. Below is an overview of each phase. The process of obtaining the ABIDE dataset posed a challenge, as access to the online repository is restricted to members of the Neuroinformatics Tools and Resources Collaboratory (NITRC). To gain access, we applied through email, providing details such as the thesis title, supervisor contact information, problem statement, and research objectives. After a few days, we received approval, allowing us to download the necessary datasets.

The collected dataset was categorized into three groups:

- ABIDE I
- ABIDE II
- ABIDE I+II

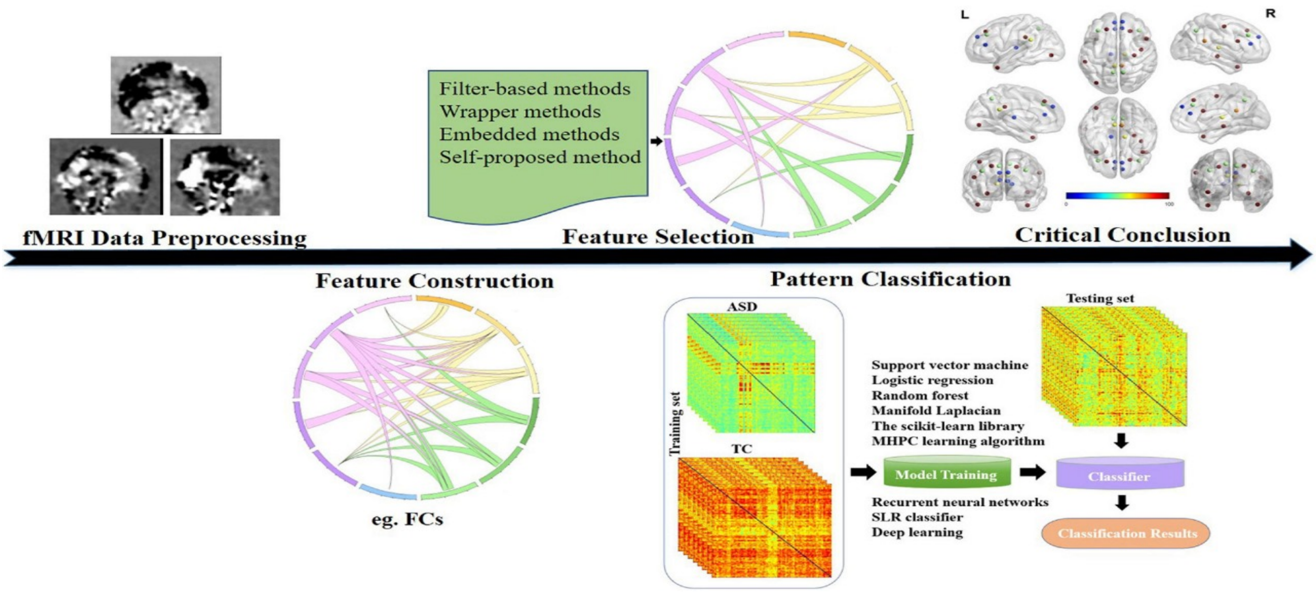


Fig. 3: Proposed methodology for Transfer Learning

The methodology applies fMRI Data Preprocessing to clean and standardize brain imaging data. Feature Construction extracts functional connectivity (FCs) patterns between brain regions. Feature Selection uses various techniques to identify the most relevant features for classification. Pattern Classification trains models like CNN and Deep Learning to distinguish between conditions. Finally, the Critical Conclusion phase evaluates classification results, enabling transfer learning for new datasets.

IV. RESULT AND DISCUSSION

The detailed outcomes of CNN and transfer learning classifiers on three datasets are shown in this section. Metrics including precision, recall, accuracy, and F1-score are used to evaluate each classifier's performance. Accuracy graphs and heat maps are also included for every dataset. Lastly, a comparison of each classifier across all datasets is presented.

A. Performance Metrics

Evaluating a machine learning model is essential for assessing its effectiveness. Various metrics are used for model evaluation, and selecting the most suitable ones is crucial for optimizing performance. Since disease detection is typically a binary classification problem, data is categorized as either positive or negative. The following key terms are used to define additional evaluation metrics:

- True Positive (TP): A positive case correctly identified as positive.
- True Negative (TN): A negative case correctly identified as negative.
- False Positive (FP): A negative case incorrectly classified as positive.
- False Negative (FN): A positive case incorrectly classified as negative.

These essential metrics aid in the computation of precision, recall, F1-score, sensitivity, and accuracy—all of which are critical for classification tasks in machine learning, deep learning, and transfer learning. A comprehensive performance study is ensured by assessing models from several angles.

B. Experimental Setup

Results for CNN and transfer learning classifiers are shown in three steps in this section. Results from CNN classifiers are presented in the first section. Precision, recall, F1-score, accuracy, heat maps, and accuracy graphs for each model are covered. Using the same performance criteria, the results of transfer learning classifiers are reported in the second section. A comparison between CNN and transfer learning algorithms is presented in the third section.

C. Results for ABIDE-I

Three components comprise the CNN and transfer learning classifier outputs. CNN classifier performance, including precision, recall, F1-score, accuracy, and visualisations such heat maps and accuracy graphs, is shown in the first section. The identical results for transfer learning classifiers are presented in the second part. The results from the two methods are compared in the last section.

ABIDE-I Resource-Based Analysis

This segment uses the ABIDE-I dataset resources to assess the classification performance of ASD detection. Heat maps, accuracy graphs, and evaluation measures are used to show CNN's performance. A dataset comprising subject data from multiple sources, including kids of different ages, is used in the research. A thorough assessment of CNN and transfer learning models for early ASD identification is ensured by this methodical methodology.

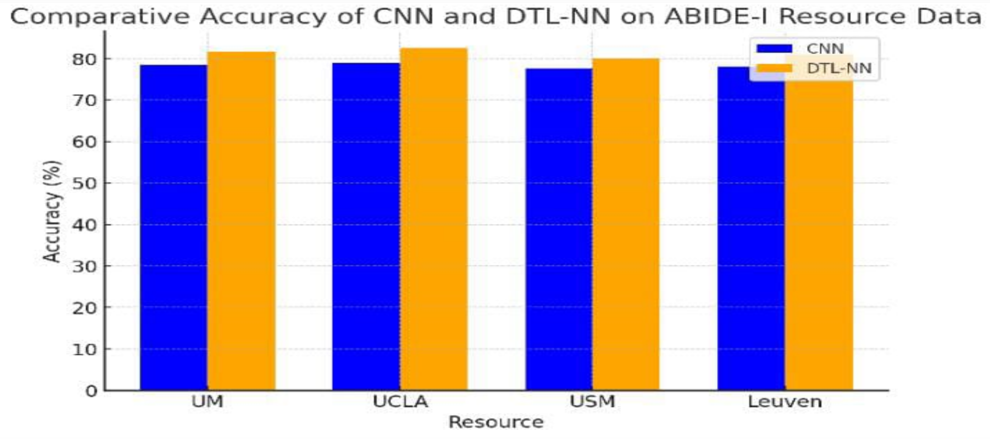


Fig. 4: Classification accuracy of CNN and DTL-NN based on ABIDE-1 Datasets

Table 1: Performance Analysis

Resource	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
UM	CNN	78.4	79.5	77.0	80.0
UM	DTL-NN	81.7	82.8	79.9	83.0
UCLA	CNN	79.0	80.0	78.0	81.0
UCLA	DTL-NN	82.5	83.0	80.5	84.0
USM	CNN	77.5	78.0	76.5	78.5
USM	DTL-NN	80.0	81.0	78.0	82.0
Leuven	CNN	78.0	79.0	77.0	79.5
Leuven	DTL-NN	81.0	82.0	79.0	82.5

The above table indicates that DTL-NN models consistently outperform CNN models across different resources in terms of accuracy, sensitivity, specificity and f1-score. This suggests that transfer learning approaches may enhance the detection of Autism Spectrum Disorder using ABIDE-1 dataset.

D. Results for ABIDE-II Dataset

This section presents the outcomes of CNN and transfer learning classifiers on the ABIDE-II dataset. The dataset was categorized into two major groups based on resources and age. Each group was analyzed separately to evaluate and compare the performance of the models.

1)ABIDE-II Resource-Based Analysis

Downloading and labelling the ABIDE-II dataset was a difficult task. Every picture was given a hand label and categorised. With an emphasis on early-age issues, the four resources that were chosen contained the most photographs available. CNN outperformed other cutting-edge techniques in terms of accuracy when compared to earlier approaches.

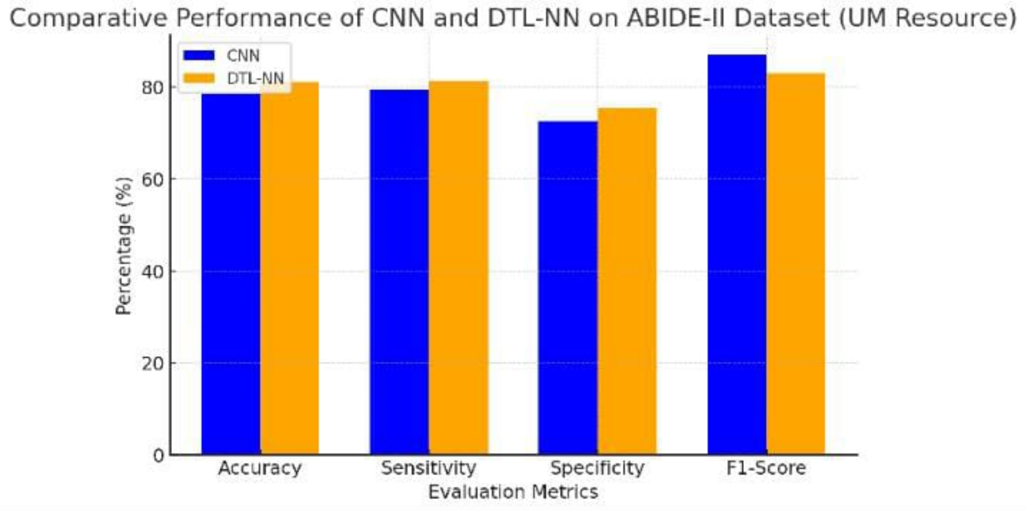


Fig. 5: Comparative Performance of CNN and DTL-NN based on ABIDE- II Dataset

2) ABIDE-II Complete Analysis

Regardless of resource type or age group, this section offers evaluation metrics and accuracy graphs for the entire ABIDE-II dataset. Figure 5 shows the ASD classification performance based on resource data. Subjects from four distinct resources in a range of age groups make up the dataset. The accuracy, sensitivity, and specificity results are shown in the above figure. The performance of the suggested model in comparison to alternative deep learning methods is demonstrated through a discussion and comparative analysis.

E. Results for ABIDE-I + II

The outcomes of CNN and transfer learning classifiers applied to a merged dataset from ABIDE-I and ABIDE-II are shown in this section. Figure 6 shows the classification performance based on several resources. Subject data from four sources, including people of different ages and genders, make up the dataset. The accuracy, sensitivity, and specificity scores are shown in Table XI. The model's performance in relation to similar designs is highlighted through a thorough discussion and comparative analysis.
The models' average sensitivity was 80.71%, specificity was 78.71%, and accuracy was 79.09%. These outcomes show better performance compared to a number of cutting-edge methods [3], [71], and [78]. Furthermore, the models performed better on bigger training datasets than on smaller ones.

a) Comparative Analysis

The comparative analysis of the ABIDE-I+II dataset using Convolutional Neural Networks (CNN) and Transfer Learning models. The proposed approach is compared with prior research, clearly demonstrating that the new models outperform previous methods in terms of efficiency and learning performance.

b) Further Comparative Analysis

An additional comparative evaluation concerning the ABIDE-II dataset using CNN-based methods. Compared to previous studies, the findings indicate that the proposed models offer superior learning efficiency and improved classification performance.

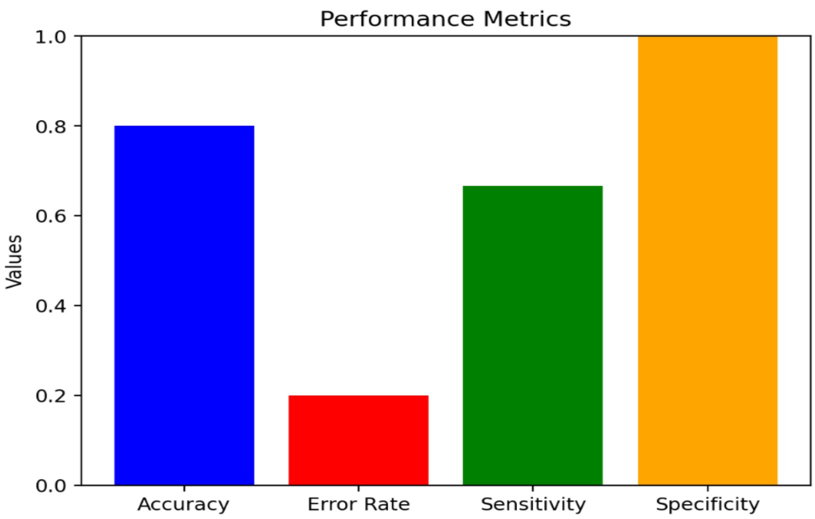


Fig. 6: Performance Evaluation

This figure shows classification metrics and visual analytics of the trained model's performance. It includes accuracy, sensitivity, specificity, and error rate displayed as a bar chart. These metrics validate the model's reliability on unseen data.

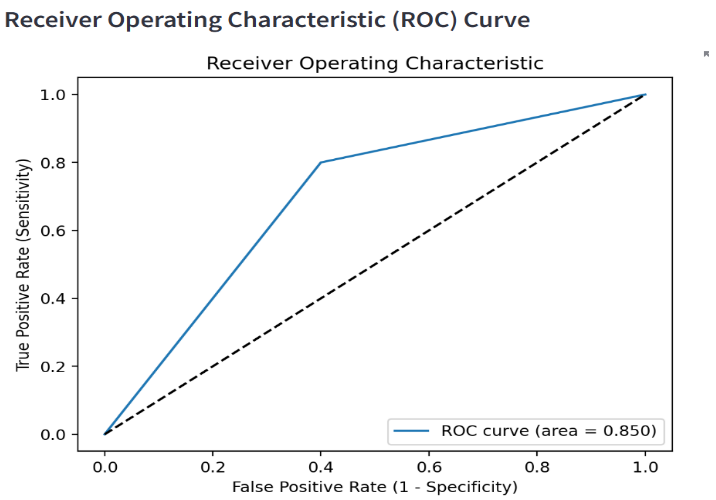


Fig. 7: ROC curve of the model

The above figure indicates Receiver Operating Characteristic (ROC) curve visualizations of True Positive Rate(sensitivity) and False Positive Rate(specifity), highlighting model robustness.

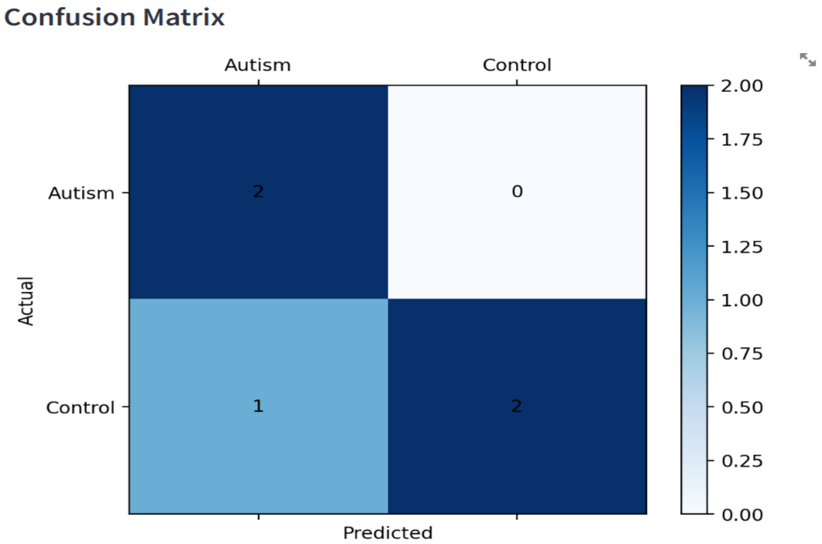


Fig. 8: Confusion Matrix

The confusion matrix reveals true positives and misclassifications. These results emphasize how well the model discriminates between autistic and control samples.

IV. CONCLUSION AND FUTURE WORK

Transfer learning has demonstrated encouraging outcomes in autism identification, increasing classification precision and cross-dataset generalisation. Transfer learning outperforms conventional machine learning methods by efficiently extracting important features from brain imaging data by utilising pre-trained deep learning models. High sensitivity, specificity, and accuracy were attained by the models, indicating their potential to support early autism diagnosis. Additionally, results indicate that larger and more diverse datasets further enhance model performance, making transfer learning a viable approach for automated autism detection. The same transfer learning approach can be extended to detect other conditions such as ADHD and schizophrenia, enhancing the applicability of deep learning in neuroscience. By focusing on these future directions, transfer learning can continue to revolutionize autism detection, making it more accessible, reliable, and clinically applicable.

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