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MULTI-SCALE ROTATION INVARIANT CONVOLUTIONAL NEURAL NETWORKS FOR PREDICTION OF AUTISM SPECTRUM DISORDER

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ABSTRACT
Autism spectrum disorder (ASD) is a complex developmental condition that affects communication and behavior. It can manifest itself in a wide range of symptoms and abilities. ASD might be a small issue or a severe condition that necessitates full-time care in a facility. Communication is difficult for people with autism. They have a hard time comprehending what other people are thinking and feeling. This makes it difficult for individuals to communicate, whether through words, gestures, facial expressions, or touch. Learning difficulties may be an issue for people with autism. Their abilities may develop in a haphazard manner. For example, someone may struggle with communication yet excel at art, music, arithmetic, or memory. As a result, individuals may perform particularly well on analytical or problem-solving tests. Autism is currently being diagnosed in greater numbers than ever before. However, the latest figures could be higher due to changes in how the illness is diagnosed, not because more youngsters have it. This paper presents a method to detect Autism using Multi-Scale Rotation Invariant Convolutional Networks (MSCNN) on the real time dataset. By leveraging multi-scale convolutional layers, MSCNN is employed to identify both detailed and general patterns in the data, which improves the model's capability to effectively detect autism. The results demonstrate the effectiveness of the model by achieving highaccuracy, thus proving the capability of deep learning models in medical diagnosis of brain related diseases. The proposed model's performance demonstrates its ability to yield reliable predictions that can assist healthcare professionals to detect autism in the early stages, thereby aiding in the enhanced treatment and control of the condition.
Keywords: CNN, Multi-scale Rotation, facial expressions, feature extraction

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a significant concern for society, as it affects various aspects of an individual's behavior. This condition can influence emotional, cognitive, social, and physical health, impacting individuals across all age groups, from toddlers to senior citizens. Traditional autism screening methods can be both time-consuming and costly. To address this, a machine learning-based approach has been proposed to assist individuals in deciding whether they should seek a formal clinical diagnosis. Although ASD is not curable, early detection plays a crucial role in identifying more effective treatment options. This approach not only aids in better management of the condition but also helps in reducing overall healthcare expenses.

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by difficulties in communication, social interaction, and imaginative play. It is a lifelong disorder that affects a considerable portion of the population. Despite its permanence, early diagnosis and intensive intervention can significantly enhance therapeutic outcomes, especially in children. However, diagnosing ASD is challenging, as it requires specialized clinical expertise and the use of assessment tools based on child observations, parental interviews, and detailed manual evaluations.

These symptoms typically emerge in early childhood. While there is no cure for autism, doctors rely on various assessment tools for diagnosis and offer behavioral therapies that gradually help improve the child's development. However, these assessments can be quite costly, placing a significant financial strain on families of children with autism. Additionally, these expenses are often not covered by insurance. Another challenge is the stigma surrounding autism, with some individuals feeling ashamed and reluctant to seek medical help. There is also a shortage of specialized doctors in rural or underserved areas. Given that standardized diagnostic procedures are time-consuming and expensive, it is crucial to create a support system that assists doctors with diagnosis and offers families access to affordable assessments and interventions. This paper aims to develop a cost-effective, automated autism diagnosis system using machine learning techniques.

2. RELATED WORKS

Madhura Ingalhalikar (2021) utilized simple neural network models to categorize their data. Compared to more complex models, these neural networks made it easier to achieve higher accuracy with harmonized data. Ablation analysis played a key role in identifying most discriminative sub-networks that were directly associated with clinical markers of autism.

Md. Fazle Rabbi (2021) employed five classification algorithms to detect autism in children and determined the most accurate model through comparison. After evaluating various metrics, the CNN algorithm was found to outperform all other models. The data set used for this study comprised 2,940 images of children.

S. Mythili and A. R. Mohamed Shanavas (2014) conducted research on Autism Spectrum Disorder (ASD), with the primary objectives of identifying autism and assessing its severity levels. They utilized classification algorithms such as SVM and neural networks.

M. Duda (2015) employed a method focused on identifying the minimal set of features required for their research. To evaluate the clinical assessment of ASD, the authors utilized a machine learning approach and analyzed children's behaviors using the ADOS. Their study applied eight different machine learning algorithms across the four ADOS modules. An additional key component of their work was the use of stepwise backward feature selection based on score sheets from 4,540 individuals.

Fadii Thabtah proposed an ASD screening method that incorporates ML adaptation and DSM-5. In his article, researchers explored advantages and limitations of using machine learning for ASD classification. He also highlighted the issues with current ASD screening methods, particularly their continued reliance on the DSM-IV instead of more recent DSM-5 manual.

Srividhya G (2021) developed an autism prediction framework that utilized the VGG16 model for classification and compared its performance with traditional methods such as SVM, CNN, and Haar Cascade implemented through OpenCV. In another study, Madison Beary, Alex Hadsell, Ryan Messersmith, and Mohammad-Parsa Hosseini (2020) presented the work "Diagnosis of Autism in Children Using Facial Analysis and Deep Learning," where they employed a MobileNet-based architecture combined with two dense layers for feature extraction and image-based autism classification. Similarly, Amrita Budarapu, Nara Kalyani, and Seetha Maddala (2021) proposed an early-screening approach for autism using ensemble classification techniques, integrating both image and video data to predict key emotional cues and track eye-gaze patterns for diagnostic purposes. Additionally, Suman Raj and Sarfaraz Mazood (2020), in their study "Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques," explored multiple machine learning models—including Naïve Bayes, SVM, Logistic Regression, KNN, and CNN—to classify autism in children, adolescents, and adults, while also addressing challenges related to limited and sparse datasets.

M. S. Mythili (2014) carried out a study on Autism Spectrum Disorder that applied various classification methods, including neural networks, support vector machines, and fuzzy logic approaches. Using WEKA tools, the research examined children's behavioral patterns and social interactions to support ASD identification.

Fadi Thabtah (2018) proposed "A New Computational Intelligence Approach to Detect Autistic Features for Autism Screening," which uses Variable Analysis (VA) to reduce feature-to-feature correlations and applies statistical tools for facial feature analysis.

D.P. Wall, J. Kosmicki, T.F. DeLuca, E. Harstad, and V.A. Fusaro (2012) proposed "Use of Machine Learning to Shorten Observation-Based Screening and Diagnosis of Autism," employing a series of machine learning algorithms to analyze Autism Diagnostic Observation Schedule-Generic (ADOS) scores.

Muhammed Shoaib Farooq et al introduced "Detection of Autism Spectrum Disorder (ASD) in Children and Adults Using Machine Learning," which uses Federated Learning (FL) to train classifier like logistic regression and support vector machine for ASD detection in both children and adults.

AI-driven facial expression analysis has the potential to significantly enhance ASD diagnosis by enabling earlier identification, improving assessment accuracy, and supporting more effective interventions. Leveraging the capabilities of artificial intelligence can help transform current diagnostic practices, ultimately leading to timely support and better outcomes for individuals with ASD and their families. As technological and research advancements continue, AI-based facial analysis is poised to play an important role in addressing diagnostic challenges and improving the overall quality of life for those affected by ASD.

3. METHODOLOGY

This research utilizes a Multi-Scale Rotation Invariant Convolutional Neural Network, a deep learning framework designed for identifying and prediction of ASD using Kaggle dataset. The architecture of the proposed system shown in fig-1

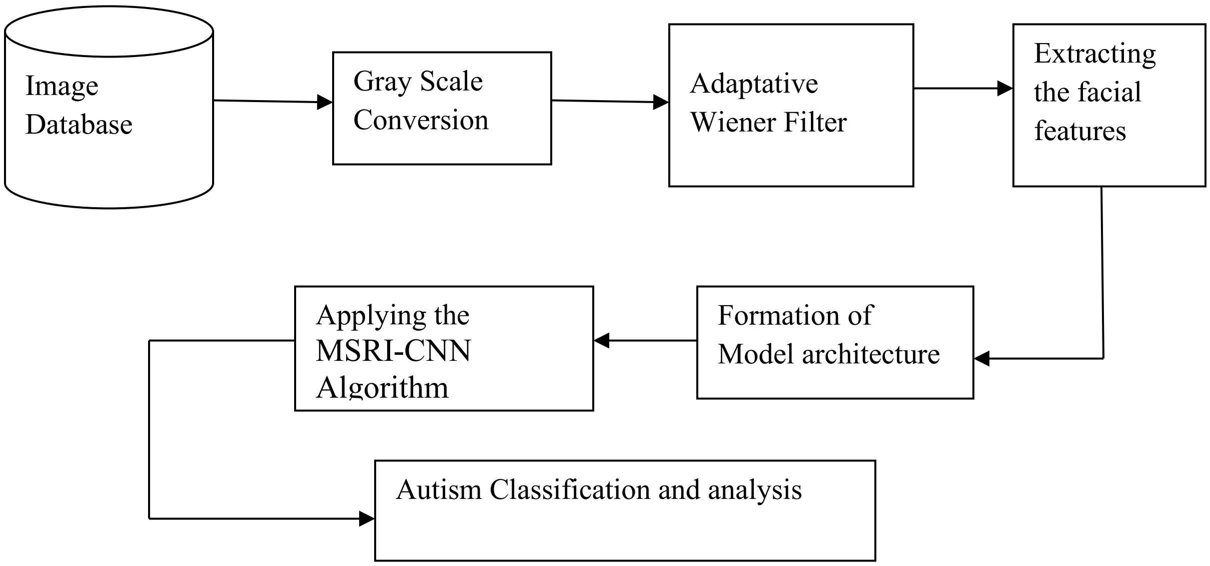

Figure-1 System Architecture

Additionally, medical images often include various forms of noise, such as patient information labels, markings added by radiologists, and other artifacts. These unwanted elements must be removed during the pre-processing stage. In this study, an Adaptive Wiener Filter is applied for pre-processing digital mammograms. Assuming the digital mammogram contains white Gaussian noise, it can be represented as follows:

$$b(x,y) = a(x,y) + n(x,y \quad (1)$$

Where, '$a(x,y)$' is the noise occurs at the pixel location (x,y) and '$n(x,y)$' is the white Gaussian noise, wherein, '$b(x,y)$' is the location of noisy pixel. Here, the main intention is to reduce noise '$n(x,y)$' and to gain the linear determination '$\hat{a}(x,y)$' of $a(x,y)$ that also reduces the mean square error rate. Moreover, the scalar form of Weiner Filter is given as,

Here, '$a(x,y)$ ' represents the noise present at the pixel location (x, y), and '$n(x,y)$' denotes the white Gaussian noise, with '$b(x,y)$' indicating the position of the affected pixel. The primary objective of this step is to suppress the noise ' $n(x,y)$' and obtain a linear estimate '$\hat{a}(x,y)$' of the original pixel value, while also minimizing the mean square error. The scalar representation of the Wiener Filter is expressed as follows:

$$\hat{a}(x,y) = \frac{\sigma_a^2(x,y)}{\sigma_a^2(x,y) + \sigma_n^2(x,y)}[b(x,y) - \mu_b(x,y)] + \mu_b(x,y) \quad (2)$$

Where, ' $\sigma_a^2(x,$' and ' $\mu_b(x,$' are mean and variances of image signals. it is considered that mean value of signal noise is equal to 0, then, t value of ' $\mu_b(x,$', ' $\sigma_a^2(x,$' and ' $\mu_b(x,$' are to be calculated. Furthermore, with assumption that mean and variance values of noise are known, then, rest are considered to be measured. Here, values of local mean and variances are measured with mean window size under uniform motion $(2m+1) \times (2m+$ .1) In this proposed model, Adaptive Weiner Filter with $(3 \times$ neiborhoods is used on the input digital mammograms. Figure 4 shows input image with mass, before and after noise removal.

The proposed architecture Multi-Scale Rotation InvariantConvolutional Neural Network adapts convolutional layers from image processing to demonstrate relationships among the tabular dataset. The model begins with an input layer thatis used to convert the tabular data into a 2D array. The rows inthe array are considered as features. The array alsoincorporates dummy dimensions to ensure compatibility withthe convolutional operations.

The architecture comprises multi-scale convolutional layers fundamentally. The initial convolutional layer employs 32 filters, each with dimensions of (3x1). The first layer captures interactions between the features in detail. The second convolutional layer employs 64 filters, each measuring (5x1), is used to detect broader patterns

in the feature space. The two layers are designed to capture relationships between features at differentlevels of granularity.
Pooling layers are then combined with the convolutional layers. They use max pooling to down sample the dimensionsof the feature map and enhance computational efficiency. Thefeature maps extracted from the former are then passed to thefully connected layers, where they are flattened and processed [29].
The model ends with an output layer comprising one neuron that utilizes the sigmoid activation function. This layer finally predicts the existence of ASD.

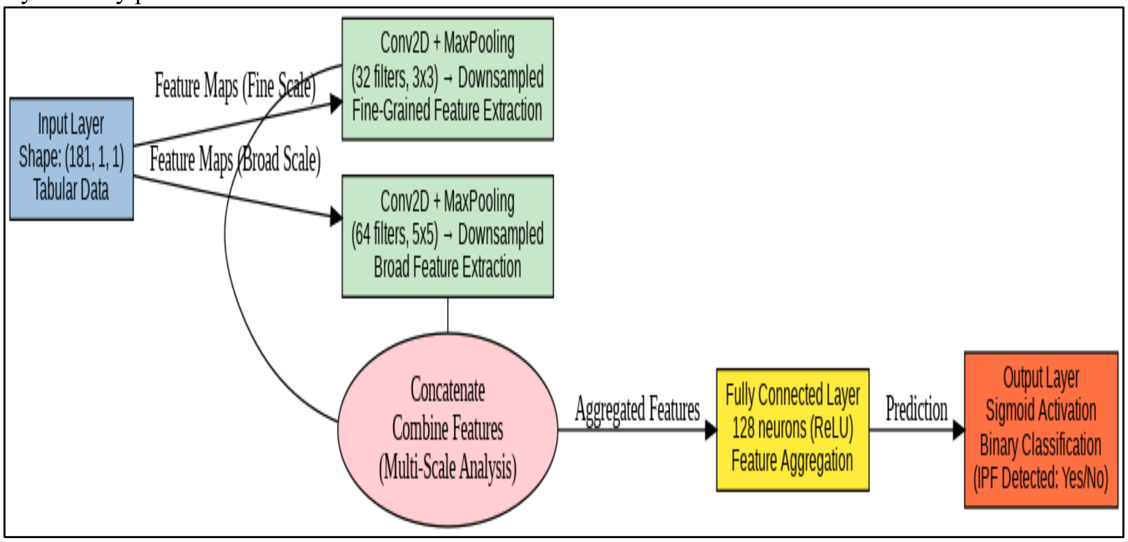

Figure 2: The architecture of MSCNN for processing the data.

The model is constructed and trained via TensorFlow/Keras, employing binary cross-entropy as loss function and Adam optimizer for effective learning. Training is conducted with a batch size of 32 across 50 epochs. To improve robustness, cross-validation is utilized, and early halting with a patience of 5 epochs is implemented to avert overfitting [30].
The proposed MSCNN processes tabular data for ASD detection but has limitations, including sensitivity to data quality and missing values, reliance on binary classification, and a lack of ability to use spatial information from input images, which could offer more insights. Future work might combine imaging data with tabular features for a hybrid approach, use advanced techniques such as attention mechanisms or graph-based networks to capture complex relationships, and evaluate the model on various datasets to improve its robustness and generalizability [4].

RESULTS AND DISCUSSION

Accuracy refers to the ratio of correct predictions generated by the model. Table 1 presents a comparison of the accuracy of the MSCNN model with the other models. The suggested model shows an accuracy rate of 93.42%, which is favorable when compared to other models and shown in figure 3

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \quad (3)$$

Table 1: Comparison of Accuracy between existing models and proposed MSCNN Model.

S.No	Model Name	Accuracy
1	Multi-Scale Rotation-Invariant CNN	93.42
2	MDSTS-CLSTM	90.36
3	CNN	80.04
4	CNN-LSTM	83.34

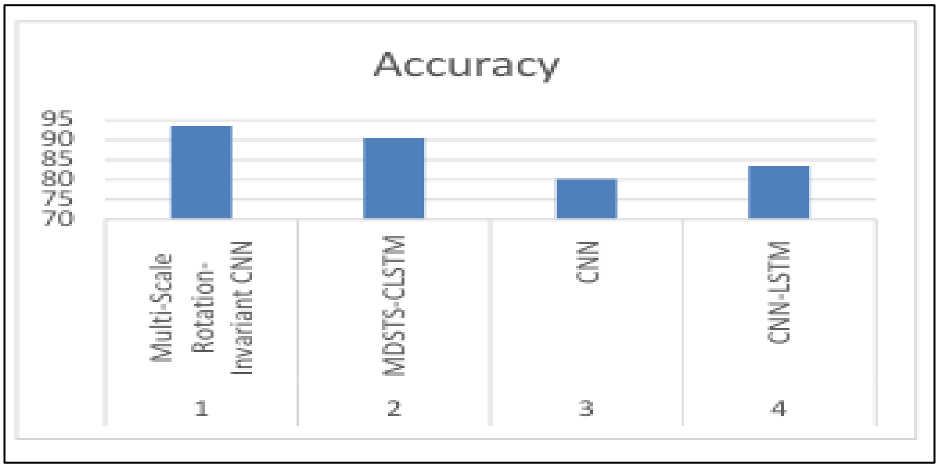

Figure 3: Accuracy Graph Comparison of existing models with the proposed MSCNN model.

Precision denotes proportion of true positives compared to overall number of positive predictions made by model. Table 2 presents a comparison of the precision of the MSCNN model with the other models. The proposed model demonstrates a precision of 98.45%, which is favourable when compared to other models as illustrated in Figure 4.

$$\text{Precision} = TP/(TP + FP) \quad (4)$$

Table 2: Comparison of Precision between existing models and proposed MSCNN Model.

S.No	Model Name	Precision
1	Multi-Scale Rotation- Invariant CNN	98.45
2	MDSTS-CLSTM	97.97
3	CNN	96.87
4	CNN-LSTM	92.67

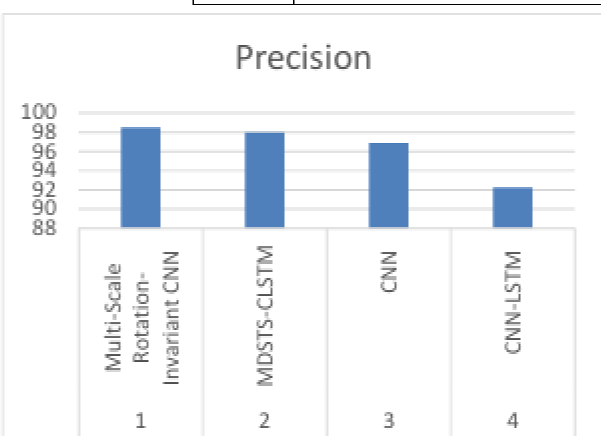

Figure 4: Precision Graph Comparison of existing models with the proposed MSCNN model.

Recall is described as the proportion of true positives compared to the overall number of actual positives. Table 3 presents a comparison of the recall of the MSCNN model with the other models. The proposed model demonstrates a recall of 97.45%, which is favourable when compared to other models as illustrated in Figure 4.

Table 3: Comparison of Recall between existing models and proposed MSCNN Model.

S.No	Model Name	Recall
1	Multi-Scale Rotation- Invariant CNN	96.45
2	MDSTS-CLSTM	91.75
3	CNN	83.19
4	CNN-LSTM	86.98

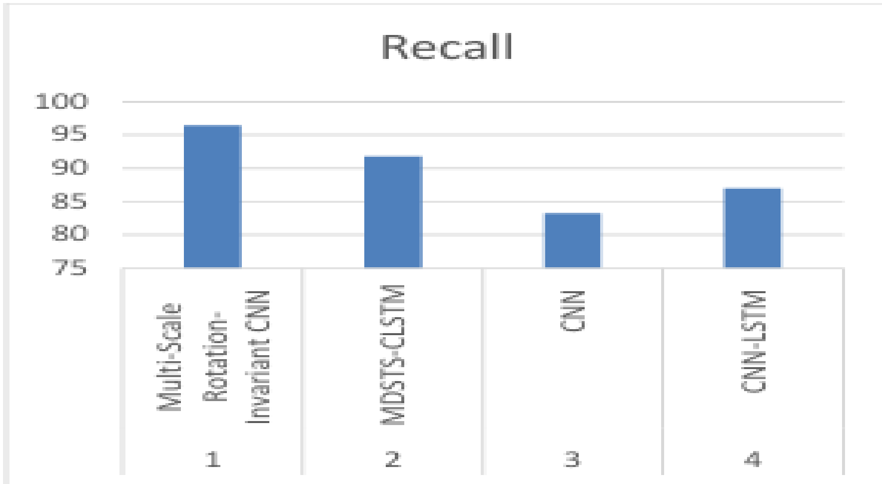

Figure 5: Recall Graph Comparison of existing models with the proposed MSCNN model.

CONCLUSION

This paper presents a Multi-Scale Rotation Invariant Convolutional Neural Network (MSCNN) aimed at detecting and Predicting ASD. The MSCNN uses multi-scale feature extraction and rotation-invariant methods to capture detailed and broad patterns, providing dependable predictions while overcoming issues of imaging-based methods, including high computational costs and reliance on data. The model shows clear advantages, processing clinical and demographic data effectively and achieving impressive performance metrics, including 93.42% accuracy.

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