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AUTOMATED AUTISM DISORDER DETECTION USING COOKOO SEARCH OPTIMIZED DCNN CLASSIFICATION FROM FACE IMAGES

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ABSTRACT

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition marked by difficulties in social interaction, communication, and behavior. Early and accurate identification of ASD is essential, as it enables timely interventions that significantly improve developmental outcomes for individuals affected. Conventional diagnostic methods often depend on subjective assessments, which result in variability and delays in diagnosis. To address these challenges, this project proposes detecting autism through a Cookoo Search-optimized Deep Convolutional Neural Network (DCNN) classification. The process starts with acquiring input images, followed by preprocessing to enhance image quality through histogram equalization and reduce noise using a Gaussian filter. Data augmentation techniques are utilized to expand the dataset's diversity, boosting the model's robustness and generalization. The Scale-Invariant Feature Transform (SIFT) is applied for feature extraction, allowing the system to capture important visual patterns from the images. For image retrieval and classification, a Deep Convolutional Neural Network (DCNN) is employed, optimized using the Cookoo Search Algorithm, which refines the classification process for improved accuracy. This combined approach enhances detection precision by improving feature extraction and optimizing network weights. Lastly, the predicted outcomes are deployed through an interface built on Streamlit , enabling real-time classification and interpretation. The proposed model shows considerable improvements in accuracy and effficiency, providing a promising solution for ASD detection. The purpose of this study is to detect autism from facial images using a deep learning model. To accurately identify autism in children, the pre-trained PSO and Cookoo Search Optimized Dcnn model, SIFT are used as feature extractors. The suggested models were trained using a publicly available dataset from Kaggle that included 3014 images of children characterized as autistic and non-autistic. The models yielded accuracies of non autistic image of accuracy, precision, recall of 96.%, 94 %, and 98%, respectively. This project is implemented using Python.

Keywords: ASD - Autism Spectrum Disorder, SIFT - Scale-Invariant Feature Transform, DCNN - Deep Convolutional Neural Network, WHO - World Health Organization, CSA - Cookoo Search Algorithm ,PYPI - Python Package Index.

I. INTRODUCTION

Autism, formally known as Autism Spectrum Disorder (ASD), is a neurological and developmental condition that primarily affects how a person perceives and interacts with the world around them. Characterized by challenges in communication, behavior, and social relationships, autism is considered a "spectrum" disorder due to the significant variability in symptoms and severity. Some individuals have minimal challenges and lead independent lives, while others require substantial support throughout their lifetime. Common symptoms include difficulty with verbal and nonverbal communication, repetitive behaviors, restricted interests, and sensitivity to sensory stimuli. The causes of autism are complex, involving both genetic and environmental factors. No single cause has been found, but gene mutations, prenatal conditions, and biological factors may contribute. Brain differences are also linked to autism, though more research is needed. Autism is usually diagnosed in early childhood, often by age two or three. Early detection is key, as therapies like behavioral, speech, and occupational therapy improve outcomes. These therapies help individuals with autism develop skills for communication, learning, and social interaction. Autism is more common than many think. Recent data indicates that approximately 1 in 36 children in the United States is diagnosed with autism, with diagnosis rates increasing globally. This rise in diagnoses be partly due to improved awareness, enhanced screening methods, and expanded diagnostic criteria. Support from family, caregivers, educators, and communities is essential for individuals with autism. Inclusive educational practices, workplace accommodations, and accessible public spaces help autistic individuals lead fulfilling lives. Embracing neurodiversity promotes a more inclusive society, one that celebrates unique perspectives and contributions. that affects individuals in various ways, presenting challenges in social interaction, communication, and behavior. First identified and described in the early 20th century by pioneering psychiatrists such as Eugen Bleuler and Leo Kanner, autism has since been recognized as a spectrum disorder, encompassing a broad range of symptoms and levels of impairment. At its core, autism is characterized by difficulties in social interaction. Individuals with autism struggle to grasp social cues and norms, such as understanding facial expressions, body language, and the nuances of conversation. This lead to challenges in initiating and maintaining relationships, as well as difficulty in understanding the perspectives and emotions of others. The social difficulties experienced by individuals with autism often lead to feelings of isolation and loneliness, highlighting the importance of fostering understanding and acceptance within society.Communication challenges are also prevalent among individuals with autism. While some have delayed speech development or never develop spoken language at all, others exhibit difficulties in using language in a meaningful way. This include the challenges in understanding and using non-literal language, such as metaphors and sarcasm, as well as difficulties in engaging in reciprocal conversation. Additionally, individuals with autism struggle with nonverbal communication, such as maintaining eye contact or using gestures, further impacting their ability to connect with others.

II. METHODOLOGY

The aim of this study was to utilize a transfer learning-based framework for recognizing autistic facial traits, with the ultimate goal of detecting the occurrence of autism spectrum disorder (ASD) in children during their early years. To accomplish this goal,we employed pre-existing deep learning models that could automatically extract sturdy characteristics that would otherwise be difficult to identify through visual scrutiny due to their complexity. These features were then processed through multiple layers, with the dense uppermost layer yielding the diagnosis of ASD.

2.1. System Architecture

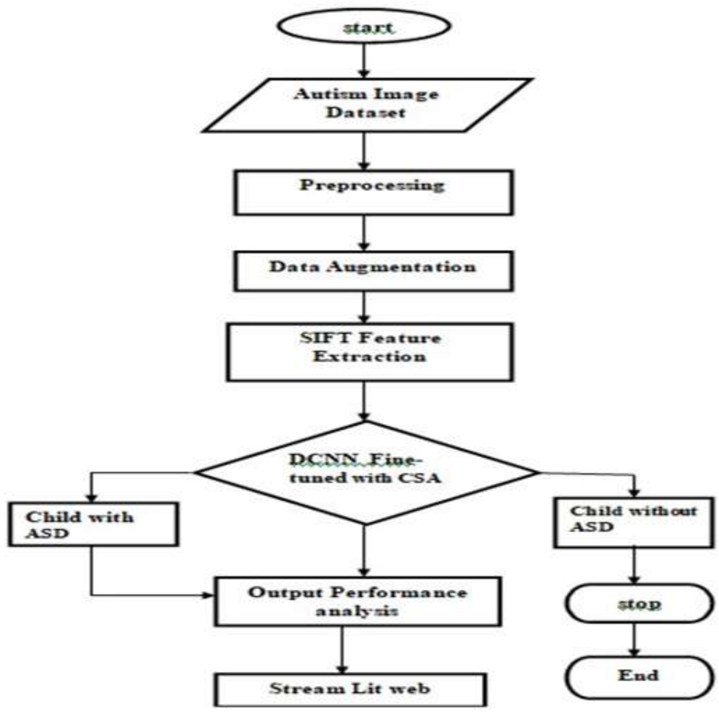

Fig 1: Flowchart of Architecture

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2.2 Dataset details

To achieve the optimal performance in deep learning models, a large dataset is essential for providing comprehensive training in diverse scenarios. the training process results in a significantly higher level of accuracy.our recommend model were developed using the autistic children dataset .which is the only the free source of kind available online in kaggle autistic children face image from immrankhan dataset .the age of children in the dataset is range from 2 to 14 years, with the majority begin between 2 to 8 years old. The dataset considered of 2D RGB images, with an almost equal ratio of the autistic class to the normal control class, and a male-to-female ratio of approximately 3:1. The images were categorized into three groups, which included the training set, testing set, and validation set. The training set contained 2536 images (86.38%), while the testing set and validation set contained300 images and 100 images respectively. In each group, the ASD and NC classes were equally represented. The provider of the images Gerry piosenka, immrankhan sourced them from an online platform.

2.3 Proposed System Block Diagram-PSO(Particle Swarm Optimization)

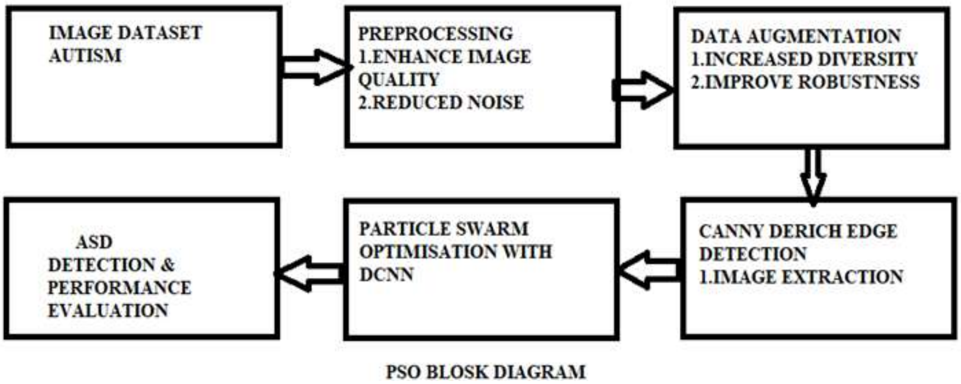

Fig 2: Proposed System Block Diagram for PSO

The proposed system for analyzing autism image datasets includes several key steps to ensure accurate predictions using techniques like Particle Swarm Optimization (PSO) and Deep Convolutional Neural Networks (DCNN). First, an autism-specific image dataset is input and preprocessed to improve quality and reduce noise. Data augmentation follows to enhance diversity and strengthen the model, creating variations like rotations, flips, and scaling. The images are then processed using Canny-Derich edge detection to extract important structural features. These features are input into a DCNN, optimized with PSO to fine-tune parameters and improve performance. Finally, the system classifies the images using the optimized model, creating a robust system for autism image analysis.

2.4 Proposed System Block Diagram-CSA(Cookoo Search Algorithm)

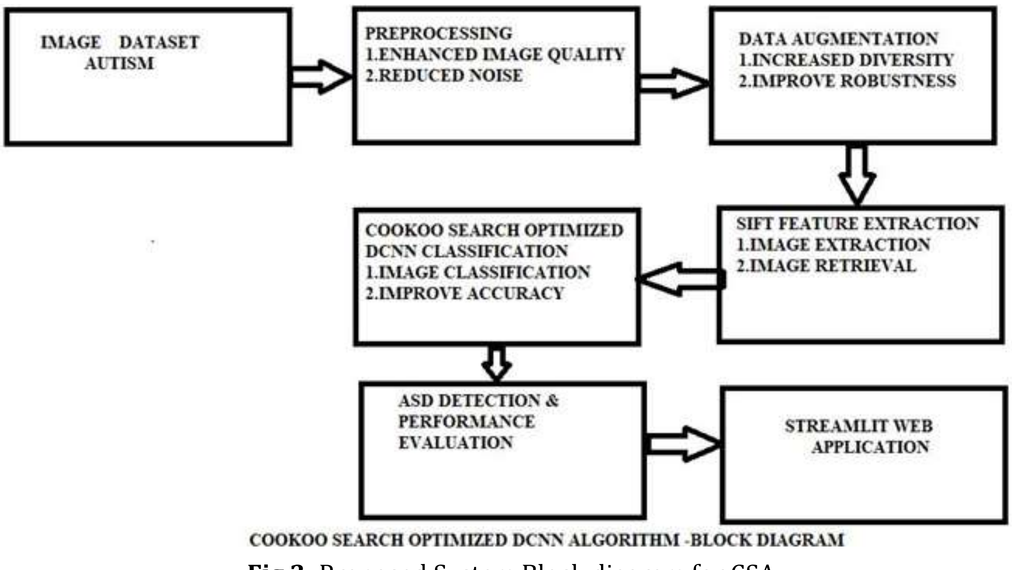

Fig 3: Proposed System Block diagram for CSA

In this proposed system detection of autism disorder through the utilization of Cookoo search optimized DCNN classification is proposed. The process begins with acquiring the input images, followed by preprocessing steps designed to enhance image quality through histogram equalization and minimize noise using Gaussian Filter. To boost the dataset's variety and improve model robustness, data augmentation techniques are applied, enhancing generalization capabilities. Next, the Scale-Invariant Feature Transform (SIFT) is utilized for feature extraction, enabling the system to identify key visual patterns within the images. For image retrieval and classification, a Deep Convolutional Neural Network (DCNN) is employed, which is further optimized using the Cookoo Search Algorithm. This optimization fine-tunes the network's classification process, leading to more accurate predictions. This hybrid approach enhances both feature extraction and the network's weight optimization, significantly improving detection accuracy. The predicted results are presented through a real-time, user-friendly interface built with Streamlit, allowing for seamless classification and interpretation. Overall, the proposed model achieves notable improvements in both accuracy and efficiency, offering a highly effective solution for detecting autism disorders.

2.5 PREPROCESSING

In the preprocessing phase for autism detection, improving image quality and reducing noise is key for better model performance. It starts with histogram equalization, which adjusts the contrast and makes features like facial structures or brain scans clearer. Then, a Gaussian filter is applied to smooth noise while keeping important edges intact. This ensures the data given to the model is clean and preserves essential information for accurate autism detection.

2.6 DATA AUGMENTATION

Data augmentation is a key technique in machine learning, used to expand a training dataset by creating modified versions of images, improving model generalization. It starts with the original dataset and applies transformations like rotation, scaling, flipping, and color changes to generate various image versions. These changes help the model recognize objects from different angles and adapt to lighting variations.

2.7 Scale Invariant Feature Transform(SIFT)

The Key features are extracted from the input images using Scale-Invariant Feature Transform (SIFT). This technique captures unique, scale-invariant features that are essential for identifying distinctive visual patterns in the dataset. These extracted features are then used in the subsequent stages for more effective classification.

2.8 The Cookoo Search Optimized Deep Convolutional Neural Network (DCNN)

The Cookoo Search Optimized Deep Convolutional Neural Network (DCNN) boosts model performance by merging optimization and deep learning. The DCNN consists of convolutional, pooling, and fully connected layers, where convolutional layers extract features, pooling reduces dimensionality, and fully connected layers make predictions. The Cookoo Search Algorithm (CSA) optimizes training by simulating cookoo birds' behavior, selecting the best solutions to minimize the loss function. It evaluates, explores randomly, and replaces poor solutions. After optimization, the best parameters train the final DCNN model, which is tested for accuracy. This method improves classification in image recognition, medical diagnosis, and object detection.

2.9 Deep Convolutional Neural Network Architecture

This classification method is based on the DCNN architecture, which includes several convolutional layers, pooling layers, and fully connected layers. The convolutional layers automatically extract important features from input images, while the pooling layers reduce the size of feature maps to improve efficiency. The final fully connected layers combine these features for classification.

III. MODELING AND ANALYSIS

The Autism Image Dataset is a specialized collection of 3,000 labeled images designed to support research and development in autism spectrum disorder (ASD) detection, therapy, and assistive technologies. The dataset includes a wide range of images categorized into facial expressions, behavioral cues, and therapy tools, providing a comprehensive foundation for computer vision tasks. Images capture diverse demographics, ensuring balanced representation across age, gender, and ethnicity. High-quality images are provided in resolutions ranging from 227x227 to 512x512 pixels, available in commonly used formats like JPEG and PNG. Each image is annotated with labels such as "autistic" or "non-autistic," and some include bounding boxes highlighting key features like facial regions or therapy objects. This dataset, sourced from Kaggle, is ideal for applications such as emotion recognition, where models learn to identify emotional responses in ASD individuals, or behavioral analysis to detect patterns indicative of autism for early diagnosis. It is also valuable for developing assistive technologies like emotion recognition systems or autism screening aids. By combining healthcare and computer vision research, the Autism Image Dataset from Kaggle provides a robust resource for creating innovative solutions to improve diagnosis, therapy, and care for individuals with ASD.

To implement the system shown in the flowchart for autism image dataset classification using deep learning, the following steps are involved.

3.1. IMAGE DATASET ACQUISITION: First, collect an autism image dataset, which includes relevant visual information for identifying autism-related characteristics.

3.2. PREPROCESSING: The raw images undergo preprocessing to enhance their quality and reduce noise. This includes histogram equalization to improve contrast and applying a Gaussian filter to reduce noise, making features more distinguishable.

3. 3.DATA AUGMENTATION: To increase the diversity and robustness of the dataset, various data augmentation techniques are applied, such as rotation, scaling, and flipping. This step helps in improving the model's generalization ability and performance by exposing it to a wider variety of data patterns.

3.4. FEATURE EXTRACTION (SIFT): Key features are extracted from the input images using Scale-Invariant Feature Transform (SIFT). This technique captures unique, scale-invariant features that are essential for identifying distinctive visual patterns in the dataset. These extracted features are then used in the subsequent stages for more effective classification.

3. 5. IMAGE RETRIEVAL: The extracted SIFT features are used for image retrieval, which facilitates the organization and selection of images based on visual similarities, further supporting the classification process.

3.6. CLASSIFICATION (Cuckoo Search Optimized DCNN): For the classification process, a Deep Convolutional Neural Network (DCNN) is employed, which is optimized using a Cuckoo Search algorithm. This optimization technique helps in tuning the DCNN parameters to enhance classification accuracy, leading to more precise predictions.

3.7 STREAMLIT WEB APPLICATION

The cookoo search optimized DCNN model classifies the images and generates a predicted output, which identifies whether the images align with autism-related features or not. Deployment on Streamlit Web App: Finally, the classification model and predicted outputs are integrated into a user-friendly web application using Streamlit. This web app allows users to easily upload images, view classification results, and interact with the model in real time. This implementation structure ensures efficient processing, robust feature extraction, and optimized classification, making it a reliable system for autism-related image analysis.

3.8 HARDWARE AND SOFTWARE COMPONENTS

SOFTWARE USED:

- Operating system: Windows 8,10.
- Coding Language: Python language
- Tool: Anaconda Jupyter

HARDWARE USED:

- System: Pentium V 2.4 GHz.
- Hard Disk: 200 GB.
- Monitor: 15 VGA Colour.
- Ram: 512 Mb.

IV. RESULT AND DISCUSION

This section relates to the outcome and discusses the hardware and software requirements needed to run the model effectively. Operating system: 64-bit Windows 7. Processing speed: In the Google Colaboratory web application environment, the pandas tool was used using an Intel(R) Core(TM) i5-2450M CPU running at 2.50

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GHz, 2501 Mhz, on two cores, and 4 GB of RAM. On the mentioned dataset, the proposed work applies machine learning algorithms to improve prediction quality. To evaluate the performance of the model and make comments on the best approach, the analysis of experiments is done using evaluation metrics including Confusion Matrix, Accuracy, Precision, Recall.

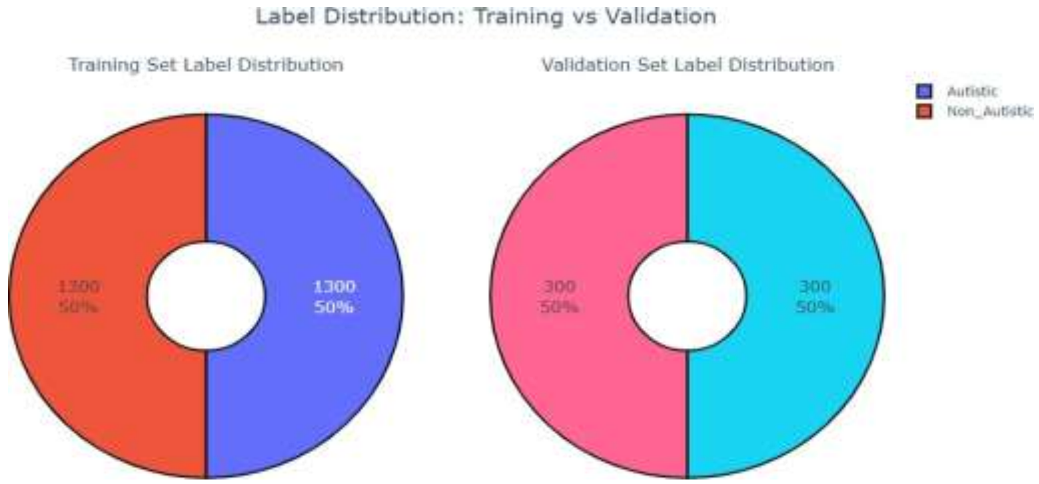

Fig 4: Label Training vs Validation dataset

The figure (4) shows the dataset has an image of training set has 1300 samples, with 50% belonging to the "Autistic" class and 50% of result belonging to the "Non-Autistic" class. The validation set also has 300 samples of the "Autistic" and "Non_Autistic" classes. This even distribution of the classes in both the training and validation sets suggests that the dataset is available from kaggle.com/imrankhan77/autistic-children facial-dataset, which is important for training and evaluating the performance of the classification model.

4. IMAGE DATASET ACQUISITION:

Image dataset acquisition is the process of gathering a large collection of images for use in training and testing machine learning models. These images are often labeled to indicate their corresponding categories or classes, enabling the model to learn patterns and make accurate predictions. The dataset may include various image types, such as photos, diagrams, or medical scans, and is essential for tasks like object detection, image classification, and facial recognition. Quality and diversity in the dataset are key factors in ensuring the model performs well in real-world applications.

Fig 5: Autistic Image vs Non Autistic Image.

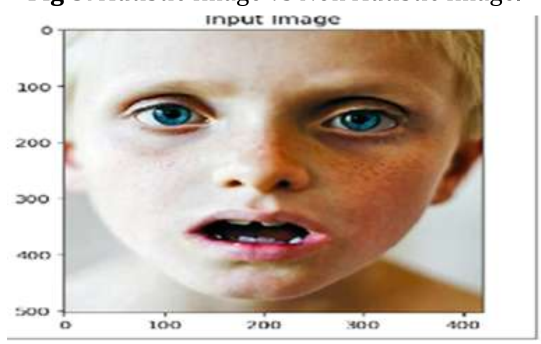

Fig 6: Input Autistic Image.

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The figure (6)shows the image which is represented in a grid-like format, with the dimensions of the image displayed below it. This suggests that the image be part of a dataset or used for some form of visual analysis .

4.1 PREPROCESSING AND DATA AUGMENTATION

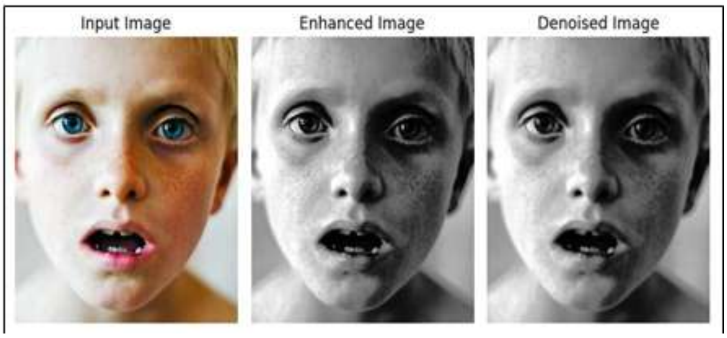

Fig 7: Preprocessed Image

The Figure (7)shows that Preprocessed image appears to have increased contrast and sharpness, highlighting the subject's facial features more prominently. This could be useful for tasks that require better visual detail or image quality.

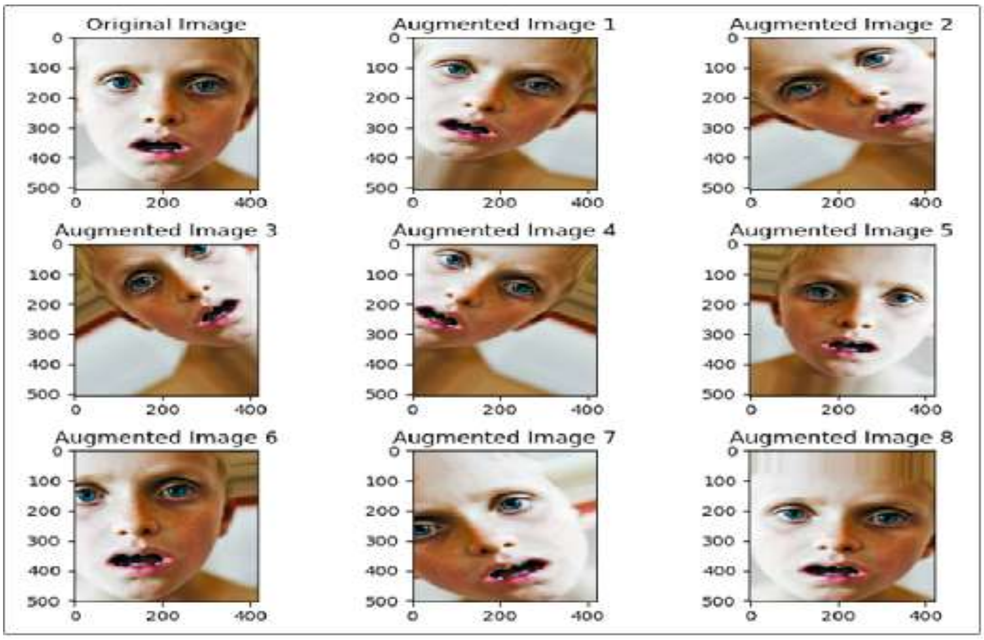

Fig 8: Data Augmentation of input image

The figure(8) shows a series of augmented versions of an original image depicting a child's face. These augmented images appear to be the result of various data augmentation techniques, which are commonly used in machine learning to enhance the diversity and robustness of training data.

4.2 SCALE INVARIANT FEATURE TRANSFORM EXTRACTION (SIFT)

SIFT (Scale-Invariant Feature Transform) is a popular algorithm used in computer vision to detect and describe local features in images. It was developed by David Lowe in 1999 and has since become one of the most widely used techniques for tasks such as object recognition, image stitching, and 3D modeling. SIFT (Scale-Invariant Feature Transform) detects and describes local features in images. The key points, like corners and edges, are invariant to scale, rotation, and some affine transformations.

The Figure (9) represent the image has 246 keypoints, and each keypoint is represented by a descriptor with a shape of (246, 12). In this case, 246 key points were identified, and each has a 128-dimensional descriptor that represents the local image patch around the keypoint. These descriptors are useful for matching key points across different images or for tasks like image stitching.

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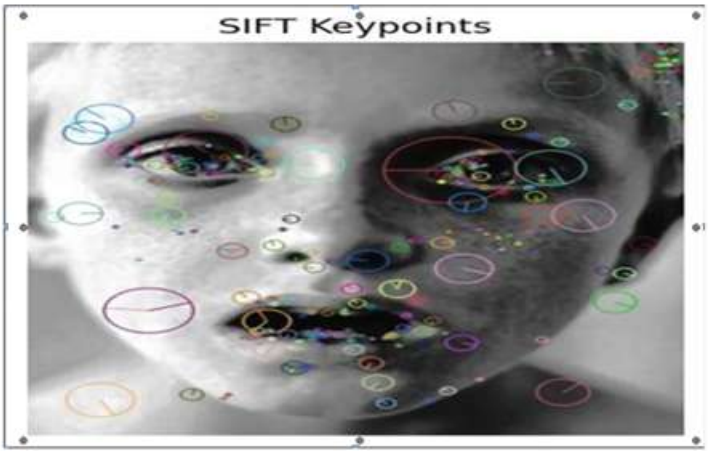

Fig 9: SIFT Extraction

(Number of keypoints:246,descriptor-128,12)

[Number of Keypoints:246,Descriptors shape:(246,12)]

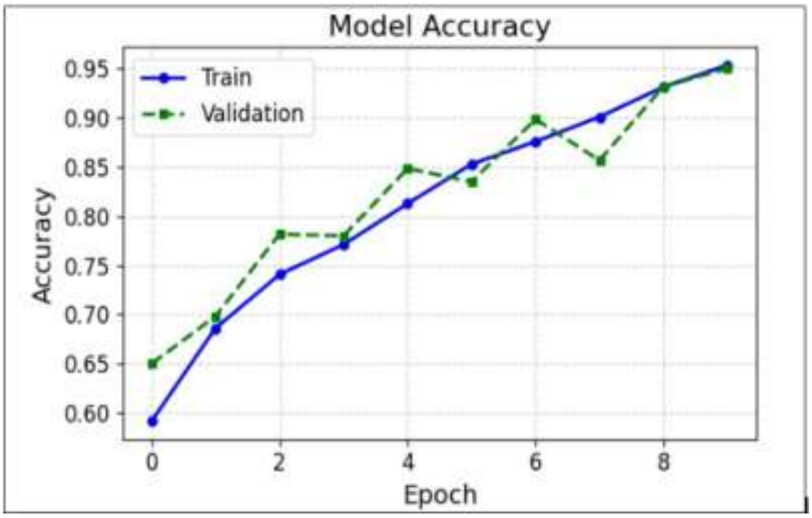

Fig 10: Model Accuracy vs Training and Validation set.

The Figure (10) and (11) illustrates that the Model accuracy plot shows the accuracy increasing as the training progresses, with the training accuracy being higher than the validation accuracy. y. The model loss plot shows the training loss decreasing rapidly, while the validation loss initially decreases but then starts to increase, indicating potential overfitting.

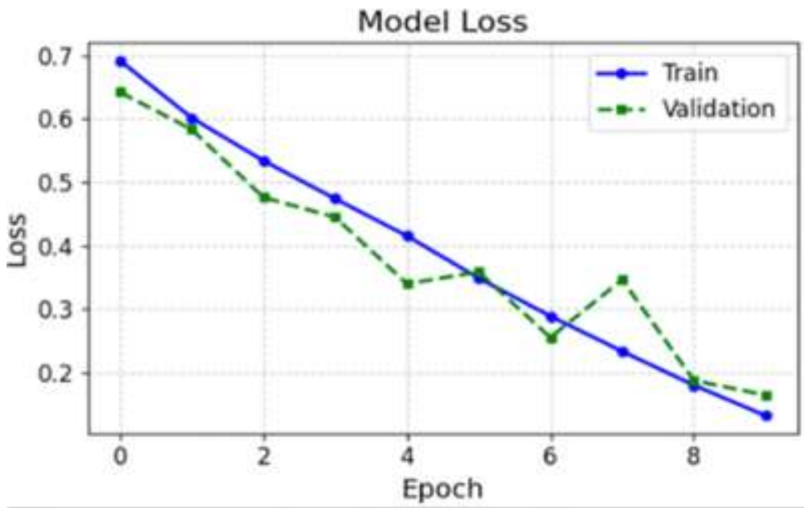

Fig 11: Model loss vs Training and Validation set.

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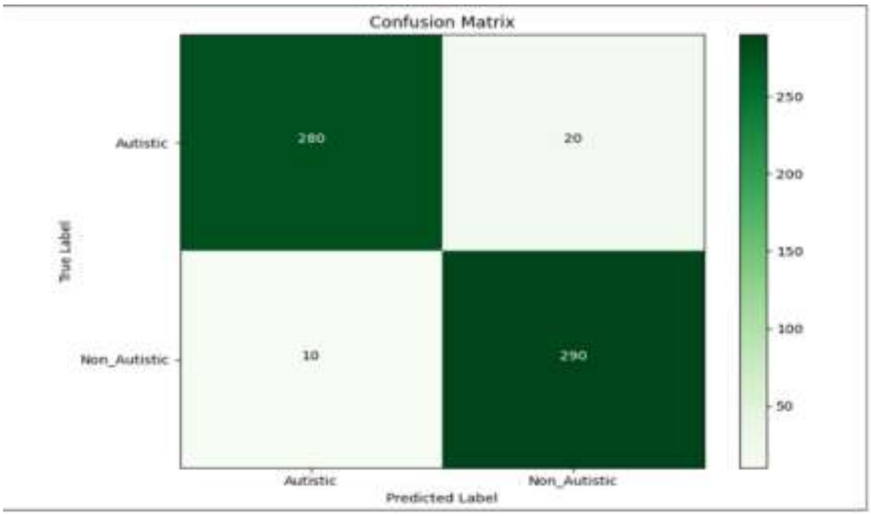

Fig 12: Confusion Matrix for CSA optimized DCNN

The figure(12) represents the matrix shows the number of true positive (280), false positive (20), false negative (10), and true negative (290) predictions made by the model. The values in the diagonal represent the correct predictions, while the off-diagonal values represent the misclassifications. A **confusion matrix** is a performance evaluation tool used to summarize the results of a classification algorithm. It compares the predicted labels with the actual labels and is particularly useful for binary and multiclass classification problems.

4.3 Components of the Confusion Matrix

Predicted Positive		Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

Where:

- True Positive (TP): Correctly predicted positive cases.
- True Negative (TN): Correctly predicted negative cases.
- False Positive (FP): Incorrectly predicted as positive (Type I error).
- False Negative (FN): Incorrectly predicted as negative (Type II error).

1. Accuracy

The Proportion of true result both true positive and true negative among the total number of cases examined.

Formula

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)}$$

Where TP = True Positive TN = True Negative FP = False Positive FN = False Negative

2. Precision

The Proportion of true positive results among all positive prediction by the model.

Formula

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

3. Recall

Recall is a metric used to evaluate a models ability to find cell positive instances, it considers all actual positives not just all correct classification.

Formula

$$\text{Recall}= TP/(TP+FP)$$

Table 1: Performance Comparison of PSO vs CSA

Algorithm	Accuracy	Precision	Recall
PSO	67	20	22
CSA	96	94	98

In the above table shows that the performance comparison of PSO with CSA in the non autistic child predicted output.

1. PSO Performance

- Accuracy : 67 % refers the non autistic child of PSO.
- Precision : 20 % refer as lower indicates a relatively low ability of PSO to correctly identify non-autistic children among all predictions.
- Recall : 22% is the only small identified percentage of the actual non- autistic children correctly.

2. CSA Performance

- Accuracy : 96 % is better overall performance compared with Pso.
- Precision : 94 % reflects CSA's strong ability to correctly identify non-autistic children, with fewer false positives.
- Recall : 98 % demonstrates CSA's better performance in identifying nearly all actual non-autistic children, outperforming PSO in this metric as well.

4.4 Performance of Confusion Matrix

A confusion matrix evaluates classification model performance by comparing actual and predicted outcomes, using metrics like True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) to calculate Accuracy, Precision, and Recall. It is a 2x2 table for binary classification and an NxN table for multiclass problems, helping to identify strengths and weaknesses, especially in imbalanced datasets.

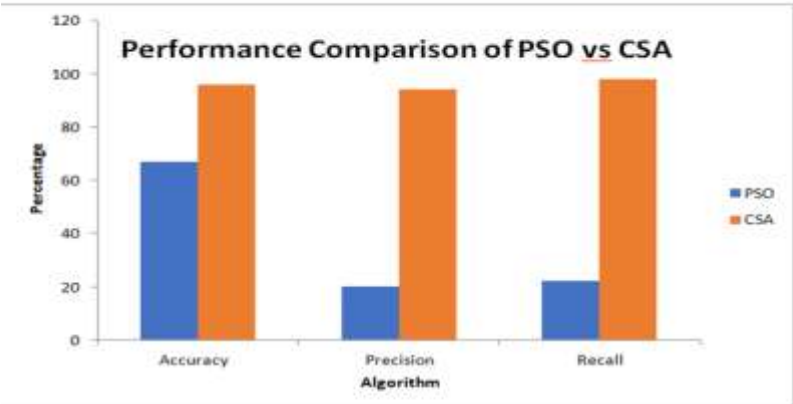

Fig 13: Performance Comparison of PSO vs CSA

Fig 14: ASD Detection of Non Autistic output Image.

The figure(14) shows the output image of a young child, and the analysis section displays the model's prediction, indicating that the individual is classified as "Non_Autistic" with a 99.93% probability.

V. CONCLUSION

This project introduces a novel method for detecting autism disorder by integrating Deep Convolutional Neural Networks (DCNN) with the Cookoo Search Algorithm for enhanced optimization. The workflow starts with image preprocessing techniques, such as histogram equalization to improve contrast and Gaussian filtering to reduce noise. Data augmentation is employed to increase the dataset's diversity, which helps to improve the model's robustness and ability to generalize. Feature extraction through Scale-Invariant Feature Transform (SIFT) ensures the capture of essential visual patterns, which are crucial for accurate classification. The DCNN, optimized by the Cuckoo Search Algorithm, fine-tunes the network's weights and improves classification accuracy, making it more efficient for autism detection. The system's deployment on Streamlit provides a user-friendly interface, enabling real-time classification and interpretation of results. This Python-based implementation shows significant advancements in detection precision and computational efficiency, offering a practical and effective tool for early diagnosis of autism disorder. This approach could greatly benefit clinical and research applications, paving the way for improved diagnostic methods. Overall, the PSO model yield accuracy of 67 % the most effective performance when trained with 5 epochs. Utilizing Cookoo Search Optimized DCNN as the optimizer yield training accuracy ,precision, recall of 96 % ,94 % ,98 % ,The Individual child image is detected as Non Autistic with 99.93% in streamlit web application.

Dataset available from link - https://www.kaggle.com/datasets/imrankhan77/autistic-children-facial.

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