DETECTION OF AUTISM SPECTRUM DISORDER USING GRAY WOLF OPTIMIZATION AND DENSENET DCNN CLASSIFICATION OF FACIAL IMAGES

Manikandan*[1], Dr.K.Padma Priya[*2], Dr.I.Muthumani[*3]
[*1]Post Graduate Student, Department of ECE,
Government College of Engineering, Tirunelveli, Tamil Nadu, India.
[*2]Assisstant Professor, Department of ECE,
Government College of Engineering, Tirunelveli, Tamil Nadu, India.
[*3]Professor, Department of ECE,
Government College of Engineering, Tirunelveli, Tamil Nadu, India.
e-mail:[*1]mani25natarajan@gmail.com,[*2]padmapriya@gcetly.ac.in,[*3]muthumani@gcetly.ac.in

Abstract: *Autism Spectrum Disorder(ASD) is known as a complex neuro-develepmental condition that necessitates accurate and early diagnosis to enable effective intervention strategies throughout the life span. Symptoms of ASD have been observed across all age groups and genders. The condition is generally initiated by stress-related factors and is carried through four primary developmental stages: childhood, toddlerhood, adolescence, and adulthood. In this study, an efficient framework is proposed for ASD detection, leveraging the increasing application of advanced deep learning and optimization techniques in medical research. A publicly available children's dataset from the Kaggle platform containing both ASD and Non-ASD facial images, is utilized for the evaluation. The software implementation is carried out using the Anaconda Navigator with the Jupyter Notebook environment, and Python IDE version 3.10 is employed.The hybrid process is initiated with an autism-specific image dataset that is preprocessed using an adaptive Gabor filter. Through this step, brightness and diversity of the input images are enhanced, and key textures and patterns are emphasized for improved feature extraction. Following this, data augmentation techniques such as rotation, flipping, scaling, and cropping are applied to increase dataset size and diversity, helping to prevent overfitting and improve model robustness. During preprocessing, features are extracted using the Maximally Stable Extremal Regions (MSER) technique, which allows for effective retrieval of stable image features. To refine the feature set, Gray Wolf Optimization (GWO) is employed for optimal feature selection, ensuring that only the most relevant characteristics are retained for classification.The selected features are then input into the DenseNet-121 deep convolutional neural network (DCNN) model for image classification. High performance is achieved, with an overall accuracy of 97%. For the ASD class, the model yields a precision of 94%, recall of 98%, F1-score of 96%, and support of 140. For the Non-ASD class, a precision of 98%, recall of 94%, and support of 140 are recorded.Finally, the predicted results are deployed through a Streamlit-based web application, enabling real-time ASD detection and user interaction.*

Keywords: ASD-Autism Spectrum Disorder ,DCNN-Deep Convolutional Neural Network ,GWO-Gray Wolf Optimizaton,Densenet121, PYPI-Python Package Indexed ,WHO-World Health Organization ,MSER- Maximally Stable Extremal Regions, AI-Artificial Intelligence, SIFT-Scale Invariant Feature Transform, CSA-Cookoo Search Algorithm, Streamlit web application, CNN-Convolutional Neural Network,SNR-Signal to Noise Ratio.

1.Introduction

ASD is a neurodevelopmental condition that significantly impacts the lives of individuals and their families[1],The term "autism" was first introduced in 1908 by psychiatrist Eugen Bleuler to describe a symptom of schizophrenia characterized by social withdrawal. In 1943,Leo Kanner published a landmark paper describing "early infantile autism," identifying a distinct group of children with social and communication difficulties, repetitive behaviors, and a preference for routine. A year after Kanner, Hans Asperger described a similar condition, now called Asperger's syndrome, with social difficulties but no major language delay. In 1994, the DSM-IV grouped autism and related disorders as Pervasive Developmental Disorders (PDD). In the 2000s, ASD diagnoses increased due to broader criteria and more awareness. The DSM-5 in 2013 combined these conditions under Autism Spectrum Disorder (ASD). Today, research focuses on the biological and genetic causes of ASD, seeing it as a wide-ranging spectrum. Support and acceptance for people with ASD have grown, and understanding continues to improve.

1.1Causes of Autism: ASD is caused by a combination of genetic and environmental factors. while the exact cause is unknown, some factors that may increase the risk of ASD.**Environmental factors;**It include prenatal exposures, maternal health conditions, and birth complications. **Prenatal exposures-**Exposure to air pollution, pesticides,**Maternal Health** Conditions such as obesity, diabetes, immune system disorders and **Birth Complications** Factors like preterm birth, low birth weight, and oxygen deprivation and fever during delivery have been associated with a heightened risk of autism.

1.2.Problem Statement:

Traditional ASD diagnosis often depends on clinicians' personal observations, which can cause differences between professionals and lead to misdiagnosis or delays. Current tools and criteria may not suit people from different languages or cultures.

1.3.Objectives:

To create a DCNN-based system using focal loss for handling class imbalance and improving diagnosis accuracy.To apply Adaptive Gabor Filtering for better contrast enhancement and noise reduction in facial images.To use MSER for detecting stable facial regions and Gray Wolf Optimization for selecting important features.To apply data augmentation techniques to diversify the dataset and strengthen model learning.To build a Streamlit app that allows users to upload images and get real-time autism detection results.

2. Methodology

2.1.Literature Survey:

In the related work section, a detailed literature survey is provided, focusing on ASD is a complex neurological condition with diverse symptoms. Early diagnosis and proper treatment can greatly improve the daily lives of children with ASD and their family condition affecting speech, behavior, and social interaction. The term "spectrum" is used because individuals with autism exhibit a wide range of symptoms and require varying levels of support. Symptoms typically appear in early childhood, often by the age of 2. Common signs include delayed speech, lack of eye contact, repetitive behaviors, hand flipping,and sensitivity to light or sound.Many individuals with autism also experience difficulty understanding body language and maintaining regular conversations. Despite these challenges, strengths such as strong memory, attention to detail, and talents in areas like mathematics, art, or music are often demonstrated.

This method trains machines to detect autism using brain images, mainly using CNNs for feature extraction instead of traditional methods. EEG signals, which show brain activity, were used as input, and classifiers like SVM, LDA, Decision Tree, Naive Bayes, and Random Forest were applied to identify ASD[1].CNN model like ResNet34, AlexNet, MobileNetV2, VGG16, and VGG19 were used to detect ASD under ages 2 to 5. Although ASD cannot be fully cured, early detection can support better behavioral and psychological development in children[2],A handwriting dataset from ASD and non-ASD individuals was used to train a deep learning model. GoogleNet helped classify tasks, even if some were incomplete. This supports early, automated ASD diagnosis for faster intervention [3].

In“ZPSO-RMLPNN” model improves ASD classification by using advanced strategies in both optimization and classification. It applies a fitness function to determine ASD likelihood and was tested on the ABIDE-II dataset. The model achieved 77.11% accuracy, outperforming previous models (67.729%). Future improvements could use nature-inspired algorithms like ant colony, CSA, or gorilla optimization for even better results [4].Home-based therapy for Romanian children age under 8 with ASD. Applied Behavior Analysis (ABA) is seen as the best treatment but needs 20 to 40 hours per week, which many families can't afford. ABA works best when practiced in the child’s everyday environment. Parents can help children with ASD improve faster, but many don’t know how. This study made software to teach parents how to give therapy at home [5].

Autism Brain Imaging Data Exchange (ABIDE) of ASD in Deep learning, especially CNNs, has been used to study brain images from the ABIDE dataset for ASD diagnosis. Improved CNN models with temporal and causal convolutions handle long-range data well and have reached up to 80% accuracy [6].This study shows that facial features can help distinguish autistic children from typically developing ones. Researchers used CNN models like MobileNet, Xception, and EfficientNet with a deep neural network to detect autism accurately, using a public dataset of children's facial images[7].

EEG signals were converted into images using Continuous Wavelet Transform (CWT). Pre-trained deep CNNs like GoogLeNet, AlexNet, MobileNet, and SqueezeNet extracted features from these images to classify ASD and typical individuals. SVM and RVM were then used for final classification. This method helps detect brain abnormalities but may delay early intervention due to processing time. EEG records the brain’s electrical activity [8]A model called CNNG,which integrates a convolutional neural network (CNN) with gated recurrent units (GRU).CNNG captures the 3D spatial features from functional magnetic resonance imaging (fMRI) data using the convolutional layers to analyze fMRI data for ASD detection. It captures spatial and temporal features and uses a sigmoid function for classification, tested on ABIDE Dataset [9].

This study presents a CNN model to classify autism (ASD) and typical development (TD). It converts 4D fMRI scans into 2D images, labels them, and uses a CNN for classification. The model was tested on the ABIDE dataset with fMRI data from 141 children aged 5 to 18[10].This study used EEG data to see if autism severity could be predicted. Researchers built brain networks and measured four types of EEG signals in children with different autism levels. They found that children with more severe symptoms had weaker connections between the front and back of the brain, but stronger connections in the front. These EEG patterns were closely linked to their autism scores.

[11].Autism is a condition that affects communication and behavior, often leading to challenges in daily life. Getting a diagnosis can take a long time about seven months. This study introduces a virtual reality (VR) tool that simulates a shopping trip with a virtual agent. It tracks how people behave during the task. Using machine learning, the system can tell apart autistic and non-autistic individuals accurately. This could help speed up and improve autism screening[12].

ASD is a brain disorder that affects behavior and thinking, creating challenges for families and society. Early and accurate diagnosis is important, but most current MRI-based methods only use local brain features. This study combines a CNN model with brain region connections (structural covariance) using MRI data to better detect ASD. The method achieved 71.8% accuracy and highlighted key brain areas like the prefrontal cortex and cerebellum. It shows that CNNs can help improve early ASD diagnosis[13]. Autism is a developmental disorder affecting communication and social skills, with rising cases in children and adults. Early diagnosis and treatment can greatly improve lives. This study uses AI and transfer learning to detect autism in children using facial images. Four CNN models—VGG19, ResNet50, InceptionV3, and NASNetLarge—were tested. NASNetLarge gave the best results with 87.5% accuracy[14]. The study found that LSTM outperformed other AI models like CNN and MLP in diagnosing ASD. It gave stable results with fewer training steps, low error, and 100% accuracy based on DSM-V standards[15].

This study aims to help diagnose autism using brain scans (fMRI) instead of just observing behavior. It uses deep learning with CNN models (VGG-16 and ResNet-50) to detect ASD from brain images. The method was tested on the ABIDE dataset and reached up to 87% accuracy. This approach gives doctors a faster, more objective way to identify autism[16].Datasets are available at kaggle platform[17].This study used fMRI data to build brain networks and proposed a new deep learning model (CNNPL) to detect autism. It combines CNN with prototype learning to better classify brain patterns. The model uses transfer learning for better training and was tested on a large multi-site ASD dataset. Results showed it outperformed other methods and could reliably detect autism across different data sources[18].

This study proposes a computer-aided system to grade autism severity in infants and toddlers (12 to 40 months) using brain activation from speech-based fMRI. It analyzes brain responses in 157 children grouped by mild, moderate, and severe ASD levels based on ADOS scores. The system focuses on specific brain areas and uses a two-stage machine learning model. It achieved up to 83% accuracy in identifying severity levels, showing potential for early and reliable autism grading[19].The aim of this paper to develop an unsupervised deep learning model that can automatically detect and classify self-stimulatory behaviors in autistic children using temporal patterns from video frames, improving early autism diagnosis without needing large labeled datasets, while also ensuring the model is interpretable and effective[20]**.**

2.2Deep Convolutional Neural Network,(DCNN): It is a type of artificial neural network primarily used for analyzing images and videos. It's a variant of Convolutional Neural Networks (CNNs) that incorporates multiple convolutional layers, allowing it to learn complex features from data. DCNNs are particularly effective in tasks like image classification, object detection, and image segmentation show in figure(a).

2.3Grey Wolf Optimization(GWO):The figure(b) explains the mechanism of metaheuristic inspired by the hunting behavior and social hierarchy of grey wolves. It's used to solve single-objective optimization problems by simulating the way a wolf pack hunts, encircles, and attacks prey. GWO classifies a population of potential solutions into four types of wolves (alpha, beta, delta, and omega) based on their fitness, with alpha being the best and omega the worst.

2.4Densenet 121: DenseNet-121 is a convolutional neural network (CNN) architecture known for its efficient feature extraction capabilities and parameter efficiency. It's a variant of the DenseNet family, specifically named for its 121 layers. DenseNet-121 is widely used in image classification tasks and is known for its ability to mitigate the vanishing gradient problem through dense connections between layers show in figure(c).

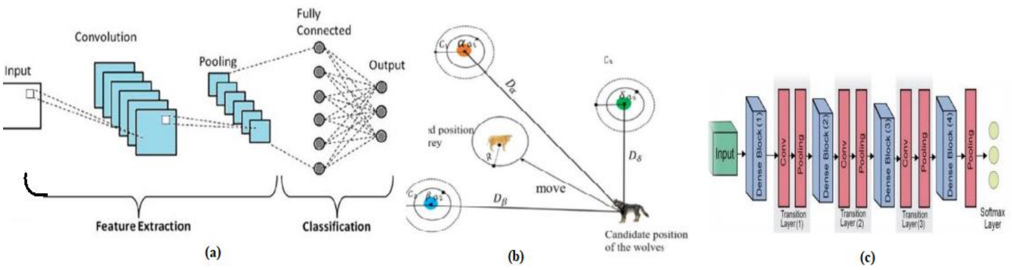

Figure.(a).DCNN model,(b)GWO model&(C)dense net 121 model

3.Modeling & Analysis

3.1 Datasets Details:

The autism children facial image dataset was collected from Kaggle, an open platform. It is a specialized dataset containing both autism and non-autism images. A total of 7,578 images were included, with 1,263 autism and non-autism images used for training, along with 6,315 data-augmented training images. For testing, 2,526 images of autism and non-autism were used, and 140 images of each class were data-augmented, resulting in a total of 280 testing images. The uploaded image was identified as a 2D (two-dimensional) image. It was captured as a flat, digital photograph containing height and width dimensions 590 × 470 pixels. Originally, the image was a 2D RGB portrait of a young child with a resolution of For processing purposes, it was converted from 224x224 to 512 × 512 pixels to make it suitable for standard input in many deep learning models. A clear frontal view of the child's face was captured, with lighting and colors evenly distributed.

3.2 Existing System:Cookoo Search Algorithm.

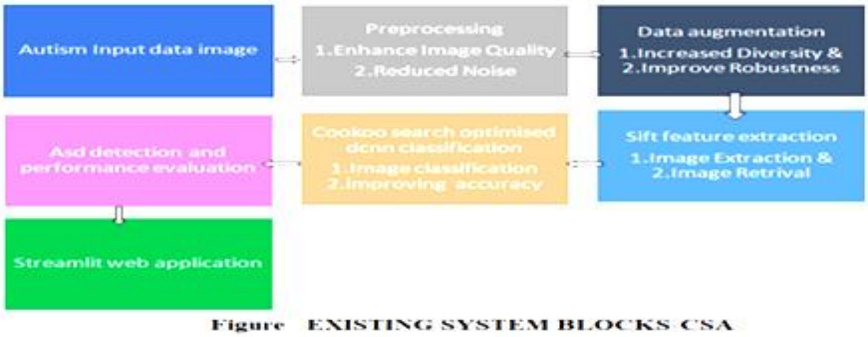

Figure1.Block Diagram of Existing System

3.2.Existing system: In this existing system detection of autism disorder through the utilization of Cuckoo 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. Then, Scale-Invariant Feature Transform (SIFT) is utilized for feature extraction, enabling the system to identify key visual patterns within the images.

3.3.System Architecture-Flowchart:

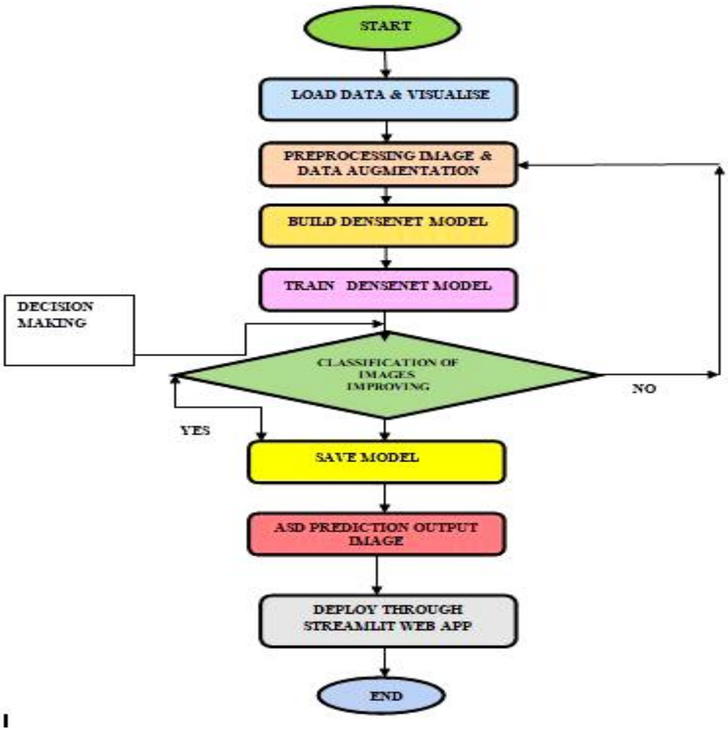

Figure 2.System Architecture

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The system architecture of the GWO with Denset net 121 is explained in the process of the proposed system using software tool- Anaconda Notebook -Jupyter 3.10 python IDE with windows 10 operating system with Hardware tool-Pentium V 2.4 ghz,512 mb RAM,Monitor-15VGA colour,HDD-200GB.

3.4.Proposed system :

Figure3.Proposed Block diagram of Gray wolf optimization with densenet121

3.3Process of the Proposed System:

1. Image Dataset Acquisition: First, Collect an autism image dataset, which includes relevant visual information for identifying autism-related characteristics.
2. Preprocessing: The raw images are subjected to preprocessing to improve their quality and minimize noise. This involves the use of an Adaptive Gabor Filter, which enhances texture details and feature visibility by emphasizing edges and reducing noise, making features easier to identify. The conventional Gabor filter emphasizes edges and textures based on specific frequency and orientation. Altering the frequency results in responses that are sensitive to fine details or, in this case, the absence of low-frequency components. Additionally, adjusting the orientation and boosting the contrast of the Gabor filter highlights unique texture patterns in the image.
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.
4. Feature Extraction (MSER): Key features are extracted from the input images using **Maximally Stable Extremal Regions (MSER)**. This technique detects stable regions across various thresholds, capturing consistent and distinctive visual structures in the dataset. These extracted features are then used in the subsequent stages for more effective classification.
5. **Feature Selection (GWO):** After feature extraction, the Gray Wolf Optimization (GWO) algorithm is employed for feature selection. Inspired by the social hierarchy and hunting behavior of gray wolves, GWO effectively identifies the most relevant and discriminative features, reducing dimensionality and enhancing the overall classification performance.

7. Classification (Densenet121): The selected features are fed into the **DenseNet121** architecture, a DCNN known for its dense connectivity pattern, where each layer receives inputs from all preceding layers. This enhances feature reuse, strengthens gradient flow, and improves classification accuracy while maintaining computational efficiency.
8.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.
The hyperparameter optimization process was used to determine the best settings such as a fixed rate of 30 epochs, a batch size of 64, and a learning rate of 0.01for model parameters like learning rate, epochs, and hidden layers on ASD datasets using deep learning frameworks including Keras, Pandas, Matplotlib, Scikit-learn, and TensorFlow. The DCNN DenseNet121 model was evaluated under these tuned conditions, and the highest achieved accuracy was reported as 97%.

3.4.Evaluation Metrics:

1.Precision:The proportion of true positive predictions out of all predicted positives.

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

2.Recall or Sensitivity: The proportion of true positive predictions out of all actual positives.

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

3.F1-score:It is the harmonic mean of precision and recall, offering a balance between the two.

$$\text{F1 Score}=2\text{x}\frac{Precision\ X\ Recall}{Precision+Recall}$$

4.Support:Support in a confusion matrix is the number of actual instances of a class in the dataset, providing valuable information about class distribution and model performance

5.Confusion matrix:
A confusion matrix is a simple table that compares a model’s predictions to the actual labels, showing how often it was correct (true positives and true negatives) versus where it made mistakes (false positives and false negatives), helping to understand and improve classification performance.

IV. RESULT ANALYSIS

Figure4.1(a).ASD&(b)NON-ASD Acquisition Image

Figure 4.1 shows how input image data for both ASD and non-ASD classes were collected. A total of 2,526 facial images were used for training the DenseNet model, while 280 images were set aside for testing. This split helps train the model and evaluate its performance on unseen data. Data preprocessing was key for the Gray Wolf Optimization (GWO) algorithm to fine-tune DenseNet's hyperparameters for better accuracy.

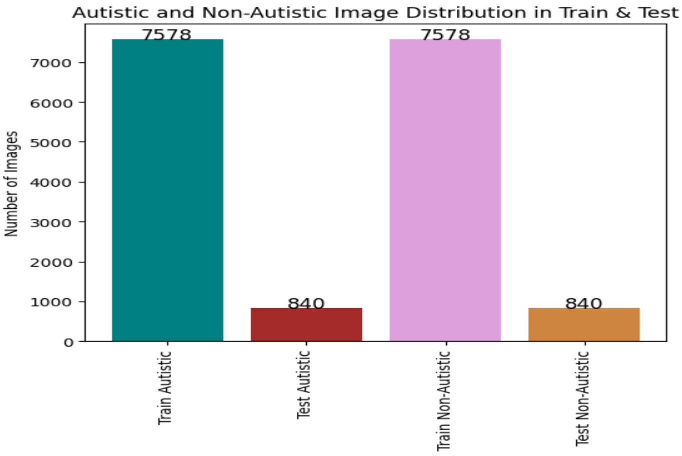

Figure 4.2 Balanced Autism Image Datasets for Training and Testing

The figure 4.2 shows a bar chart of autistic and non-autistic facial images in the training and testing datasets. Non-autistic images are well balanced, with 7578 in each set. Autistic images are fewer but evenly split (840 each), indicating a class imbalance that should be considered during model development

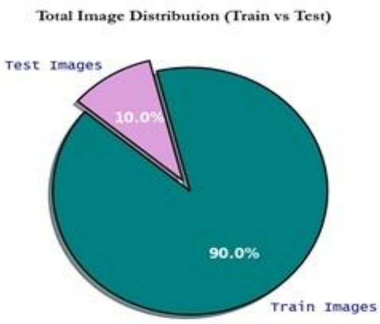

Fig 4.3 training vs testing image data splits

fig.4. 4color space tranformation of facial image

Figure 4.3Training vs. Testing Image Data Split & Figure 4.4 Colour Space Transformations of a Facial Image

Fig.4.5 ImageData augmentation techniques

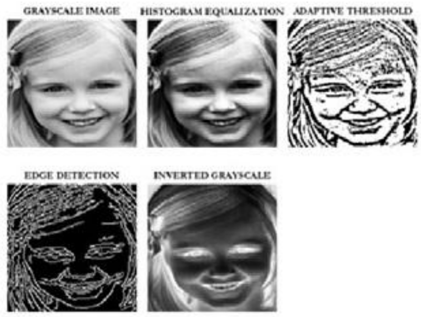

fig.4.6 Exploring Advanced Image Preprocessing operation

Figure 4.5 &4.6 data augmentation and image preprocessing techniques.

In figure 4.3, the dataset division is depicted using a pie chart: 90% of the images are allocated for training the model, while the remaining 10% are reserved for testing&In Figure 4.4, various colour space representations of the original photograph are presented. The standard RGB (Red, Green, Blue) image is shown alongside a BGR (Blue, Green, Red) version, where the red and blue channels are swapped, resulting in a noticeable color shift. Additionally, the image is converted to grayscale, representing intensity levels, and to the HSV (Hue, Saturation, Value) colour space, which separates colour information into distinct components.

The figure 4.5 implies collection showcases several fundamental image augmentation methods applied to the original RGB image. These techniques include resizing to a different dimension, applying a blurring filter to reduce high-frequency details, and sharpening to enhance edges. Furthermore, the image is horizontally flipped, creating a mirror image, and rotated by 45 degrees, introducing a change in orientation. These augmentations are often used to increase the diversity of training data for computer vision models.

The figure 4.6 shows advanced image processing steps on a grayscale image. Histogram equalization improves contrast, adaptive thresholding creates a binary image based on local brightness, and edge detection highlights key structures. Adaptive thresholding converts the image to a binary format based on local intensity variations. Edge detection highlights significant intensity changes, outlining the image's structures. Finally, the inverted grayscale shows the negative of the image, where light areas become dark and vice versa.

Figure 4.7 Gobar filter Response varying with parameter

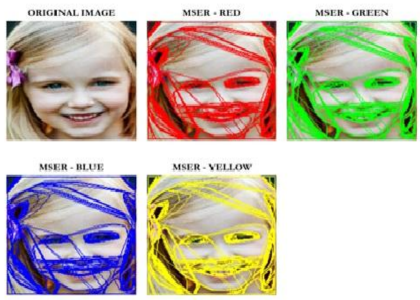

Figure 4.8 (MSER) in Different Color Channels

Figure 4.7 Gabor Filter Responses with Varying Parameters & Figure 4.8(MSER) in Different Color Channels

The figure 4.7 shows how Gabor filters highlight edges and textures by changing frequency and orientation. and. Figure 4.8 shows how the MSER method detects stable regions in different color channels of an image, with results marked in red, green, blue, and yellow, MSER detects stable connected regions in an image based on their intensity. Here, the detected regions are overlaid on the original image, highlighted in red, green, blue, and yellow, showcasing how the extracted features vary across the red, green, and blue colour components of the image.

classification report

	precision	recall	f1-score	support
0	0.94	0.98	0.96	140
1	0.98	0.94	0.96	140
accuracy			0.97	280
macro avg	0.96	0.98	0.97	280
weighted avg	0.96	0.97	0.97	280

Figure4.9Classification Performance Report .

The figure 4.9 summarizes the performance of a classification model for classes 0 and 1. It shows precision, recall, F1-score, and support for each class. The model achieved 0.97 overall accuracy. Macro and weighted averages for precision, recall, and F1-score are also reported, giving an overall view of the model's effectiveness across both classes.

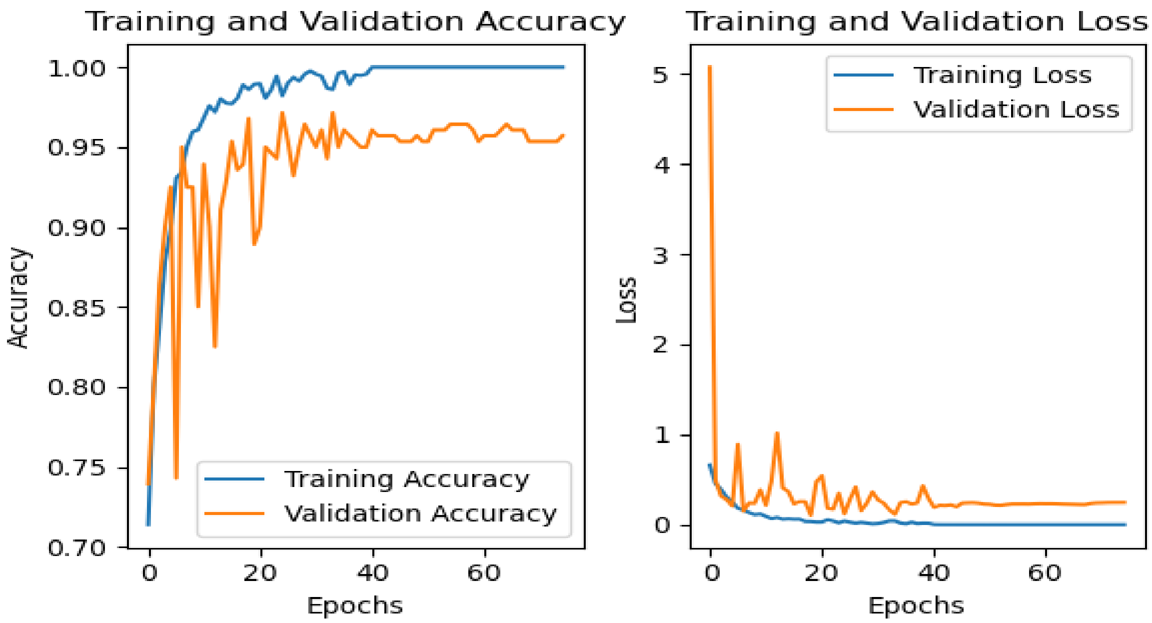

Figure 4.10 Model Training Performance

The figure 4.10 shows training and validation accuracy (left) and loss (right) over 70 epochs. Training accuracy rises steadily and levels off near 1.0, while validation accuracy fluctuates but reaches a high value. Training loss drops quickly toward zero, and validation loss decreases, then varies slightly before stabilizing at a low level. These trends indicate effective learning and good generalization.

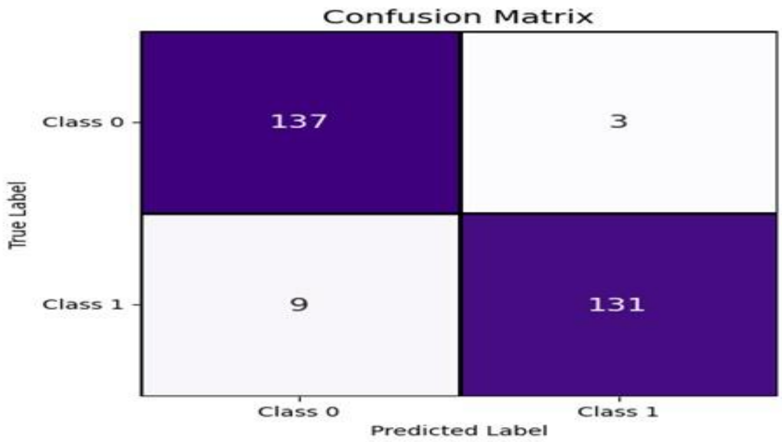

Figure4.11 Confusion matrix of ASD &NON ASD

Figure 4.11 Confusion Matrix

The figure 4.11 show the confusion matrix provides a detailed breakdown of the classification model's predictions. The confusion matrix is structured such that the rows denote the actual class labels (Class 0 and Class 1), while the columns represent the predicted class labels. Correct classifications are indicated by the diagonal elements: 137 instances of Class 0 and 131 instances of Class 1 were accurately predicted. Misclassifications are reflected in the off-diagonal elements: 3 instances of Class 0 were incorrectly predicted as Class 1, and 9 instances of Class 1 were incorrectly predicted as Class 0.

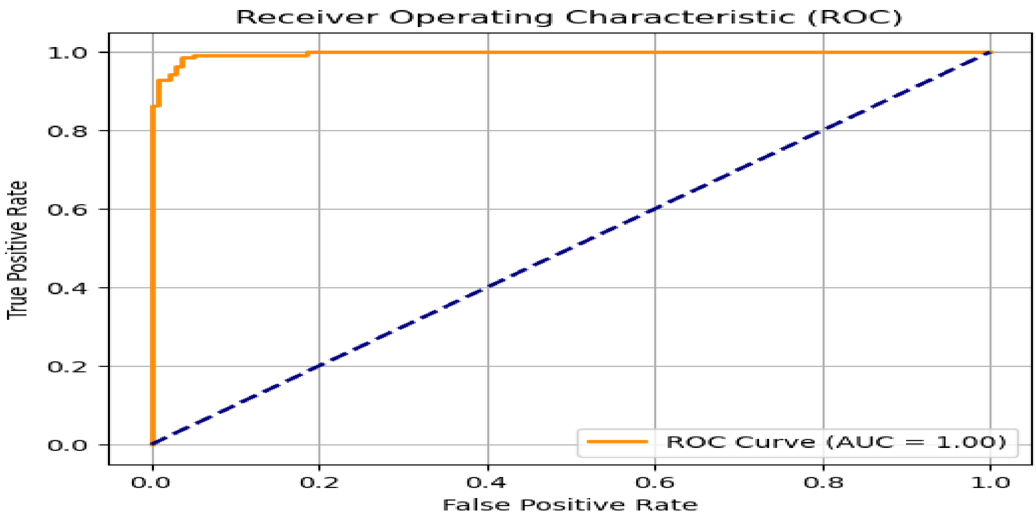

Figure 4.12 Receiver Operating Characteristic (ROC) Curve Analysis.

The Figure 4.12 illustrates the Receiver Operating Characteristic (ROC) curve for the classification model. The orange line represents the ROC curve, plotting the True Positive Rate against the False Positive Rate at various threshold settings. The area under this curve (AUC) is 1.00, indicating perfect discriminatory ability of the model to distinguish between the two classes. The dashed blue line represents the ROC curve of a random classifier (AUC = 0.5), against which the model's performance is compared.

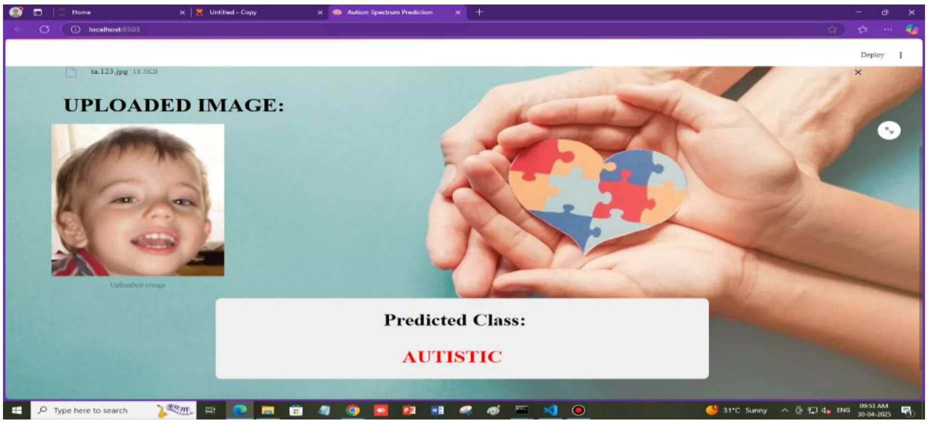

Figure 4.13 Autism Spectrum Prediction of ASD Display**.**

The above figure 4.13 shows a Streamlit-based web app for Autism Spectrum Prediction. Users can upload facial images by dragging files or browsing their device. It supports JPG, JPEG, and PNG formats up to 200MB. The "Uploaded Image:" section displays the input image, and the "Predicted Class:" section shows the model’s result, here labeled as "AUTISTIC," showing the model’s ability to classify different inputs clearly.

5.Conclusion & Future Work

A strong and efficient method for automatically detecting ASD, using facial images was introduced. Adaptive Gabor Filters were used for image preprocessing to improve quality and feature variety. Important and stable features were extracted using the Maximally Stable Extremal Regions (MSER) technique. The feature set was optimized using Gray Wolf Optimization (GWO) to reduce complexity and select the most useful features. These features were then given to the DenseNet-121 deep learning model for classification. Focal loss was applied to manage class imbalance and improve accuracy. The model's performance was measured using Accuracy, Precision, Recall, and F1-Score, and high effectiveness was shown in detecting ASD. A web application using Streamlit was also created to allow real-time detection through a simple interface. A complete system combining preprocessing, feature extraction, optimization, and deep learning was successfully developed for early ASD screening. In the future, the model can be improved by using data from different groups to reduce bias, making the model's decisions easier to understand, and combining other types of data like genetic or behavior information with images to better detect and understand autism.

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