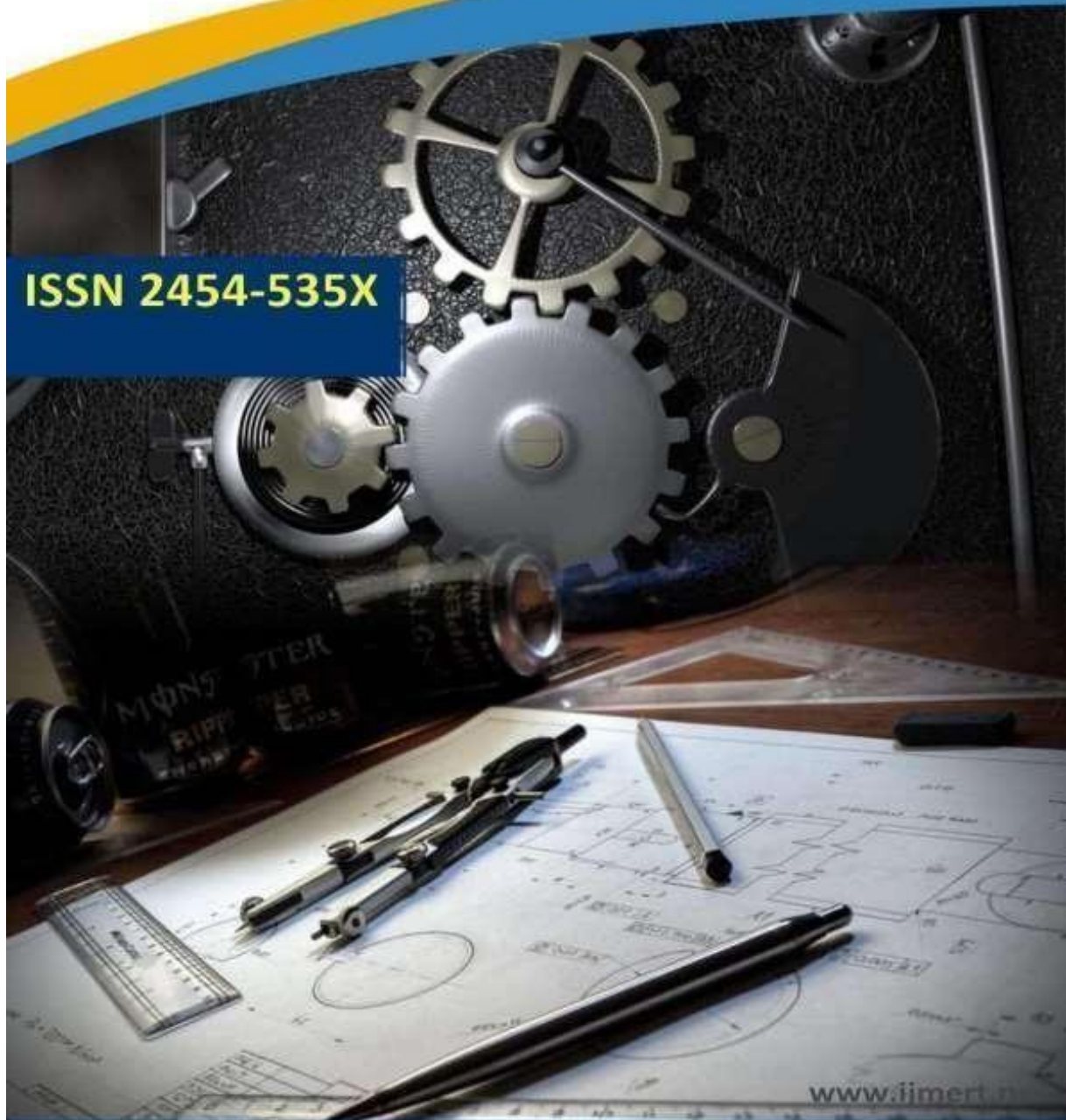




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Using Convolutional Neural Networks for Autism Spectrum Disorder Detection

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Abstract- Research in this area focuses on convolutional neural networks (CNNs) and their potential utility in the diagnosis of autism spectrum disorder. To begin, the provided image is enhanced by pre-processing. In doing so, we eliminate background noise and boost contrast. The data augmentation technique is relocating a pre-processed image to increase the dataset's diversity and resilience. After data augmentation, feature extraction is performed using a scale-invariant feature transform (SIFT). SIFT maintains unique image points regardless of changes in scale, rotation, or illumination. By using these features throughout training, the CNN model becomes better at spotting ASD patterns. The objective of building and training the CNN model is to accurately classify input images as either having ASD or not. Through a series of iterative model improvements and validations, the CNN achieves impressive performance in identifying ASD-related traits in facial images. Thanks to the trained CNN model's seamless integration, users may see the outcome inside the app interface of the Streamlit online application.

1.INTRODUCTION

People with autism spectrum disorder (ASD) have trouble interacting with others, have trouble communicating, and act out in social situations. Autism, which was first recognized by Swiss psychiatrist Eugen Bleuler in the early 1900s and later characterized by Austrian psychiatrist Leo Kanner, is now known as a spectrum illness that encompasses a broad range of symptoms and impairment levels. Fundamentally, autistic people have trouble communicating and interacting with others. People on the autism spectrum may have difficulty interacting normally with others because they have trouble reading social signs including tone of voice, facial expressions, and body language. Feelings of loneliness and trouble making and keeping friends may result from this. Autistic people often struggle with communication as well. Some may never acquire the ability to speak, while others may have a delay. Some people may struggle to recognize metaphors or sarcasm because of their language processing issues. Some autistic people may also have trouble or never use nonverbal cues like eye contact and gestures to convey meaning. People on the autism spectrum often have limited interests and repetitive habits in addition to difficulties with social interaction and communication. Repetitive gestures (such as flapping one's hands or rocking back and forth), strict routines, and hyper-focus on one's surroundings are all symptoms of these behaviors. Although these actions may provide autistic people a feeling of stability and regularity, they can also get in the way of their day-to-day lives and their relationships with others. The idea of the autism spectrum arose from the fact that people with autism might exhibit a broad range of symptoms. Some people may have low levels of functioning and need a lot of help getting about every day, while others may be much more independent. Because of this diversity, it is critical to learn about and accommodate the specific needs of each autistic person. The exact origins of autism are still a mystery, however current thinking points to a mix of hereditary and environmental variables. The precise processes behind autism are complicated and multi-faceted, while several environmental factors and genetic alterations have been associated to an elevated risk of the illness. Many people with autism have special skills and abilities, despite the difficulties that come with the disorder. Some people have extraordinary imagination and focus on detail, which manifests itself in their exceptional performance in artistic, musical, or mathematical fields. Society may aid autistic people in thriving and adding their unique ideas to the world by cultivating an accepting and inclusive atmosphere.

2.LITERATURE SURVEY

Zohre Sharif et al [2024] have suggested training the computer to perform diagnoses similar to those of a human brain. Without using the traditional feature extraction techniques, we evaluate the best ways to use



deep learning in the autism diagnostic feature extraction block. In order to verify the data that is accessible for feature extraction, a CNN structure is used. Machine learning classifiers RF, decision tree (DT), simple Bayes classification (GNB), support vector machine (SVM), and linear discriminant analysis (LDA) are used for classification. The acronym ASD describes a group of neurodevelopmental disorders characterized by deficits in social communication and repetitive activities. Electroencephalography (EEG) signals are a useful tool for autism diagnosis since they properly portray brain activity.

Israr Ahmad et al [2024] have shown and evaluated the efficacy of several pre-trained convolutional neural networks for ASD diagnosis, including ResNet34, ResNet50, AlexNet, MobileNetV2, VGG16, and VGG19. Persistent challenges in social interaction, limited behaviors, speech, and nonverbal communication define autism spectrum disorder (ASD), a complex psychiatric condition. The effects of this condition and the intensity of its symptoms differ from one individual to another. In the majority of instances, symptoms of autism spectrum disorder (ASD) start showing up between the ages of 2 and 5, and they persist all the way into adulthood. Although there is currently no treatment for this illness, research has shown that identifying children with this syndrome at an early age helps them preserve their psychological and behavioral development. In an effort to speed up the screening process, experts are looking at several machine learning approaches, with a focus on convolutional neural networks. One potential framework for ASD diagnosis is convolutional neural networks.

Amna Hendr et al [2023] created a handwritten dataset including individuals who have autism spectrum disorder (ASD) and those who do not in order to use it for deep learning classification. Subjects were asked to complete a range of handwriting activities, including sketching and writing, which formed the basis of the dataset that was developed. An automated ASD diagnostic approach based on deep learning was proposed using the dataset. Every subject's handwriting task in the dataset is trained and categorized using the GoogleNet transfer learning algorithm. This is done because in real-life situations, a person with autism spectrum disorder (ASD) may not always follow instructions when it comes to writing. The medical and health communities have long struggled with the enormous problem of autism spectrum disorder (ASD) early diagnosis. In order to intervene early and treat ASD effectively, an early diagnosis is essential.

Mihaela Chistol et al [2023] outline the theoretical and practical concepts needed to answer the following research question: "How can educational software be developed to offer therapeutic interventions for children under the age of eight in Romania who have been diagnosed with autism spectrum disorder?" Oh no! According to the U.S. Applied behavior analysis (ABA) is considered the most effective treatment for autism, according to the U.S. Department of Health and Human Services. But families can't afford the therapy since it demands a substantial time commitment of 20 to 40 hours each week. Applied behavior analysis (ABA) therapists stress the need of using treatment strategies in the child's natural setting to ensure their continued efficacy. Hence, it is necessary to enhance treatment in the home setting, where the children spend the majority of their time. A kid's skill development is accelerated when a parent or caregiver acts as a co-therapist and works with the child during practice sessions. Unfortunately, a lot of parents don't know much about treatment plans. Designed and built instructional software to fill this need for home-based therapeutic treatments for children in Romania diagnosed with Autism Spectrum Disorder (ASD).

Rasha Kashef et al [2022] suggest using deep learning to extract patterns of brain activity indicative of autism spectrum disorder (ASD) from a massive collection of brain images. Images of the brain are retrieved from the Autism Brain Imaging Data Exchange (ABIDE) database. In order to diagnose autism spectrum disorder (ASD), the convolutional neural network (CNN) architecture studies patterns of functional connectivity between various brain regions. The improved CNN is well-suited for sequential data with broad receptive fields of reception because it utilizes blocks of temporal convolutional layers that use casual convolutions and dilations. According to the findings of the experiments, the ECNN may reach an accuracy level of 80% or higher.

K. K. Mujeeb Rahman et al [2022] have shown that static characteristics derived from photos of autistic children's faces may be used as a biomarker to differentiate them from normally developing youngsters. The complex neurological developmental disease known as autism spectrum disorder (ASD) may show itself in many ways. Early diagnosis and adequate medical care greatly improved the everyday lives of both the kid diagnosed with ASD and their parents. For the purpose of reliably identifying children with autism, a DNN model was used as a binary classifier in conjunction with five pre-trained convolutional neural network (CNN) models: MobileNet, Xception, EfficientNetB0, EfficientNetB1, and EfficientNetB2. Additionally, the proposed models were trained using a publically accessible dataset that included facial images of children with autism spectrum disorder (ASD) and controls that were categorized as either non-autistic or autistic.



Qaysar Mohi ud Din et al [2022] have proposed CWT-based scalograms for electroencephalogram (EEG) data. For feature extraction and scalogram classification from EEG signals of both typically developing and autism spectrum disorder (ASD) participants, pre-trained deep Convolutional Neural Networks (CNNs) including GoogLeNet, AlexNet, MobileNet, and SqueezeNet were used. Classification of the features extracted by the deep CNNs was also accomplished using the Support Vector Machine (SVM) algorithm and the Relevance Vector Machine (RVM). Autism spectrum disorder (ASD) is currently diagnosed clinically based on behavioral assessment, which delays early intervention due to the lag between abnormal brain development and the corresponding behavioral traits. One method for diagnosing neurological diseases is electroencephalography (EEG), which examines the brain's electrical activity. There is a difference between the EEG signals of people with autism spectrum disorder (ASD) and those of typically developing participants, according to research.

Wenjing Jiang et al [2022] used a CNNG, a classification network for ASDs that combines convolutional neural networks (CNNs) with gate recurrent units (GRUs). In the first step, CNNG uses the 3D CNN's convolutional layer to extract the spatial properties of functional magnetic resonance imaging (fMRI) data. Next, CNNG uses the GRU to extract the time-related features, which are then classified using the sigmoid function. An worldwide public dataset known as the Autism Brain Imaging Data Exchange (ABIDE) was used to verify CNNG's performance. Patients and their families are profoundly impacted by autism spectrum disorder (ASD), a neurodevelopmental illness. The early detection of autism spectrum disorder allows for successful intervention throughout the early stages of the disease's progression.

Asmaa Nasser Darweesh et al [2022] have detailed a convolutional neural network that can distinguish between ASD and TD. There are several limits to the present approach of diagnosing ASD, which relies on clinical interviews and observations of behaviors, features, and skills. There is a critical need for automated methods that can accurately distinguish between ASD and normally developing (TD) children, especially in light of the present difficulties in determining the causes and processes linked with ASD. First, there's preprocessing; second, there's 2D functional MRI image conversion; and last, there's ASD or TD labeling. The third and final step is the CNN, which sorts pictures into ASD and TD categories. This network pulls its resting-state functional magnetic resonance imaging (fMRI) data from the famous autism brain-imaging data exchange (ABIDE) dataset, which includes 141 participants ranging in age from 5 to 18.

Yangsong Zhang et al [2022] have shown if electroencephalography (EEG) measures may predict the severity of ASD symptoms. The EEG brain networks were built and four kinds of EEG metrics were computed using a publically accessible dataset. Next, we contrasted the variations in brain networks between normally developing (TD) children and children with autism spectrum disorder (ASD) of different severity levels, as measured by high and low autism diagnostic observation schedule (ADOS) scores. The next step was to see whether the EEG measures may help with ASD symptom severity prediction. Disruptions in the large-scale brain network's ability to integrate and separate relevant pieces of information are hallmarks of autism spectrum disorder (ASD). Although research on the different levels of ASD symptoms has focused on associated behaviors and brain activity, there is still a need for further investigation into the best ways to predict the severity of ASD symptoms.

Marta Robles et al [2022] have detailed a method for assisting in the diagnosis of autism spectrum disorders via the use of embodied agents in virtual reality social interactions, namely a shopping experience. Behavioral reactions are monitored and documented during this routine engagement. Dissimilarities in social interaction, communication, and repetitive behaviors describe Autism Spectrum Disorders (ASD), also known as Autism Spectrum Conditions (ASD). Because of this, many people on the autism spectrum have difficulty coping with daily life, which may lead to emotional difficulties, loss of work, or substance abuse. Waiting around for a diagnosis—which averaged out to almost seven months—is a major issue with patient support and treatment. Importantly, the patient's level of support improved in proportion to the timing of the intervention.

Jingjing Gao et al [2021] developed a novel approach to ASD patient classification using sMRI data from the ABIDE collaboration by integrating individual structural covariance networks with convolutional neural networks (CNNs). In addition, Grad-CAM, which stands for gradient-weighted class activation mapping, was used to define the relative importance of the characteristics used for classification. Patients, their families, and society as a whole bear the brunt of autism spectrum disorder (ASD), a group of neurodevelopmental diseases characterized by impaired social interaction, communication, and conduct. In order to discover and intervene early, it is crucial to correctly distinguish individuals with ASD from normal controls. Nevertheless, the majority of the current structural MRI (sMRI)-based ASD diagnostic algorithms rely on independent local morphological characteristics without taking into account the patterns of feature covariance across areas.



A.Kalaiselvi et al [2021] have detailed the use of transfer learning for the diagnosis of autism spectrum disorder in youngsters. The technique employs four distinct convolutional neural network (CNN) architectures—the VGG19, Resnet50, InceptionV3, and NASNetLarge models—for autism identification. For training, testing, and validation purposes, we provide a dataset that includes pictures of autistic and typically developing children's faces. Impairments in social interaction and communication are hallmarks of the cruel developmental condition known as autism. Autism is becoming more common in both children and adults. People with autism, whether they are toddlers or adults, undergo profound behavioral changes as a result of early diagnosis and intense treatment, the origins of which are still a mystery.

Vikas Khullar et al [2021] With the purpose of improving the accuracy of autism spectrum disorder diagnoses and severity assessments, have created a portable diagnostic system based on deep neural networks (DNNs). Using a dataset based on DSM V, the system for ASD detection was first trained using DNN methods such a convolutional neural network, long short term memory (LSTM), and multilayer perceptron (MLP). While training and validating the DNN algorithms, their performance was evaluated using metrics such as precision, recall, accuracy, loss, mean squared error (MSE), and area under the curve (AUC). Afterwards, the handheld diagnostic system (HDS) was programmed using the best DNN algorithm out of all the ones that were tried, and its performance was evaluated. Twenty people with ASD and twenty normally developing (TD) persons were used to verify the stability of DNN based HDS.

R. Nur Syahindah Husna et al [2021] summary of the ASD biomarker that is derived from functional magnetic resonance imaging (fMRI) scans of the nervous system, which assist in the diagnosis of ASD by medical professionals. In order to determine whether patients have ASD or not and to extract robust features from functional magnetic resonance imaging (fMRI) neuroimages, this research used a deep learning technique derived from Convolutional Neural Network (CNN) variations. After that, it uses the accuracy of the pre-processed photos to determine the neural pattern classification. Brain imaging studies of people with autism spectrum disorder (ASD) were conducted using the Autism Brain Imaging Data Exchange (ABIDE) dataset. Disability in the development of certain problems, including social communication, creativity, and patients' skills to establish connections, is defined as Autism Spectrum Disorders (ASDs). The frequency of autism spectrum disorder diagnoses in Malaysia continues to rise annually. Without the capacity to diagnose Ff, clinicians often examine ASD patients based on history and behavior observation.

I. Al-Hiyali et al [2021] have provided an explanation of several convolutional neural networks that may be used to identify ASD using classification of temporal dynamic characteristics and to enhance the outcomes of ASD predictions. The Autism Brain Imaging Data Exchange (ABIDE) recruited 82 patients from 3 locations, 41 of whom had ASD and 41 of whom were considered normal. Extracting blood-oxygen-level-dependent (BOLD) signals requires selecting areas of the default mode network (DMN). The time-frequency components of the collected BOLD signals are transformed into scalogram pictures and fed into feature extraction pre-trained convolutional neural networks like ResNet18, DenseNet201, GoogLeNet, and ResNet101. The characteristics that were retrieved are trained using two classifiers: K-nearest neighbours (KNN) and support vector machine (SVM).

Yin Liang et al [2021] have tackled the problem of diagnosing autism spectrum disorder (ASD) using a new architecture that combines a convolutional neural network (CNN) with a prototype learning network (CNNPL). In the CNNPL, a simple feature extractor called classic CNN was used at the bottom, and at the top, several prototypes were automatically learned to represent different categories using the features. To learn the parameters of the CNN feature extractor and the prototypes simultaneously, a generalized prototype loss based on distance cross-entropy was used. Using prototype matching, the categorization was carried out. In the fine-tuning phase that followed, CNNPL was equipped with a transfer learning method to aid in model training during weight initialization.

Reem Haweel et al [2021] provide new evidence for the use of brain activity analysis in speech experiments as a basis for computer-assisted grading in children aged 12–40 months. At the outset, we use the ADOS calibrated severity score to categorize the 157 autistic participants into three groups: those with a mild case, those with a moderate case, and those with a severe case. The hypoactivation of the cingulate gyri, primary auditory cortex, angular gyrus, and superior temporal cortex increases as the severity of autism spectrum disorder (ASD) rises. Recordings of activation in the left hemisphere likewise show less lateralization. Further local and global feature extraction in the ASD grading system is limited to these ROI zones. Among people with autism spectrum disorder (ASD), there is a broad range of linguistic impairments. When combined with competent clinical judgment, the Autism Diagnostic Observation Schedule (ADOS) has emerged as the diagnostic gold standard for autism.



Shuaibing Liang et al [2021] have taken use of the breakthrough by free-supervising the use of temporal coherence between neighboring frames and establishing a global discriminative margin to extract characteristics of slow-changing discriminative self-stimulatory behaviors. Quite a few people suffer with autism spectrum disorder. The outlook for autistic patients depends on prompt diagnosis. Autism spectrum disorder (ASD) is most often diagnosed by observing the child's behavior. Being able to pick up on these behavioral signals takes years of clinical training for doctors. Recent developments in deep learning algorithms and hardware have made it possible to use AI technology to detect and record self-stimulatory behaviors automatically. The efficiency of physicians' job was enhanced by using this method. Unfortunately, there is a dearth of large-scale annotated data for training the model in the self-stimulatory behavior study area. Unsupervised machine learning approaches are therefore used.

Guangtao Nie et al [2021] have discussed a C3I system that allows youngsters with ASD to practice IJA skills in an immersive environment. C3I is an innovative computerized intervention system that combines human and computer-administered intervention by including a caregiver into the instructional loop. Six caregiver-child dyads with autism spectrum disorder participated in the feasibility study. The performance of IJA showed a nearly statistically significant improvement with a modest effect size. C3I was shown not to raise caregiver stress, according to physiology-based stress analysis. Response to joint attention (RJA) has been the primary focus of the few technology-based JA studies that have shown promise. From the standpoint of technology-based interventions, the second crucial part of JA—the beginning of joint attention (IJA)—has gotten less consideration.

METHODOLOGY

3.1 BLOCK DIAGRAM OF EXISTING SYSTEM

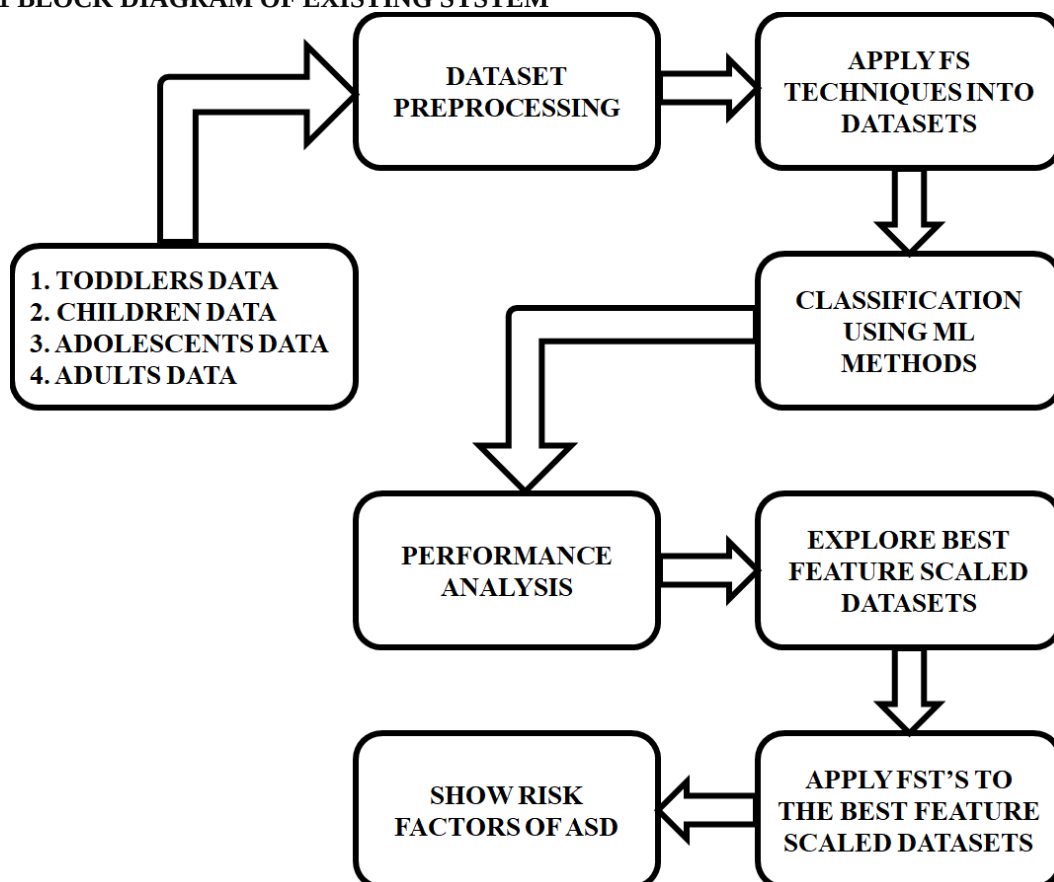


Figure 1Block Diagram of Existing System

A machine learning framework was created inside this preexisting system to identify Autism Spectrum Disorders in their early stages. To aid in the early diagnosis of ASD, this approach provides a solid foundation for assessing ML methods. By using four different Feature Scaling (FS) procedures and eight efficient ML



algorithms, our trials on conventional ASD datasets reveal noteworthy discoveries. Some notable tools used are Ada Boost (AB), Toddlers, and Linear Discriminant Analysis (LDA) for Adolescents. In addition, Feature Selection Techniques (FSTs) bring attention to important traits that are necessary for effective ASD prediction. The potential effectiveness of the framework in early ASD identification is highlighted by this extensive study, which offers significant assistance for healthcare practitioners in screening ASD patients.

3.2 DATASET

Choosing and maintaining relevant datasets is crucial for building and testing prediction models in the quest for early-stage ASD identification using machine learning frameworks. Clinical evaluations, behavioral observations, neuroimaging scans, and genetic profiles are all important parts of a comprehensive dataset that should include ASD in all its complexity. To make sure the models can be applied to different populations, the dataset has to be big enough and representative enough to include a variety of demographic variables, symptom severity, and developmental milestones. If we want to know how ASD symptoms develop over time and what signs to look for as early warning signs, we need longitudinal data. Annotating and categorizing data accurately and consistently is also important, since errors or inconsistencies may introduce biases and make machine learning models less effective. Research on the early diagnosis of autism spectrum disorder (ASD) may benefit greatly from large-scale, high-quality datasets that can be made available via scientific community collaboration and data-sharing programs.

3.3 PREPROCESSING

When it comes to early-stage ASD identification using a machine learning framework, preprocessing is essential for getting the data ready for training and evaluating the models. At this point, you should be well on your way to improving the input data's quality and usefulness. The first step in maintaining the reliability of a dataset is to use data cleaning procedures to remove any errors, outliers, or missing information. After that, in order to make the models more efficient and easier to understand, we use feature selection and extraction techniques to find the right variables and lower the dimensionality. Because ASD is so diverse, it may be necessary to use specific preprocessing methods to standardize and harmonize data across multiple modalities before merging multimodal data sources including genetic profiles, clinical evaluations, and neuroimaging scans. When working with sparse or unbalanced data, data augmentation techniques may be used to make the training dataset more representative of the real world. The input features should be normalized and scaled as part of the preprocessing processes to reduce the impact of different units and scales. This will help the model learn from the data efficiently, independent of the size of individual characteristics. To optimize the performance and generalizability of machine learning models for early-stage identification of ASD, strong preprocessing approaches are necessary. This will enable clinicians to reliably identify at-risk patients and permit timely treatments.

3.4 DRAWBACKS OF EXISTING SYSTEM

ASD prediction using feature selection techniques (FSTs) to determine which features are relevant. It is an oversimplification of the complexity and heterogeneity of ASD to assume that these qualities are fundamental across all age groups and populations. Although the ML framework does not provide encouraging outcomes when evaluating the significance of features or accuracy.

3.5 PROPOSED SYSTEM

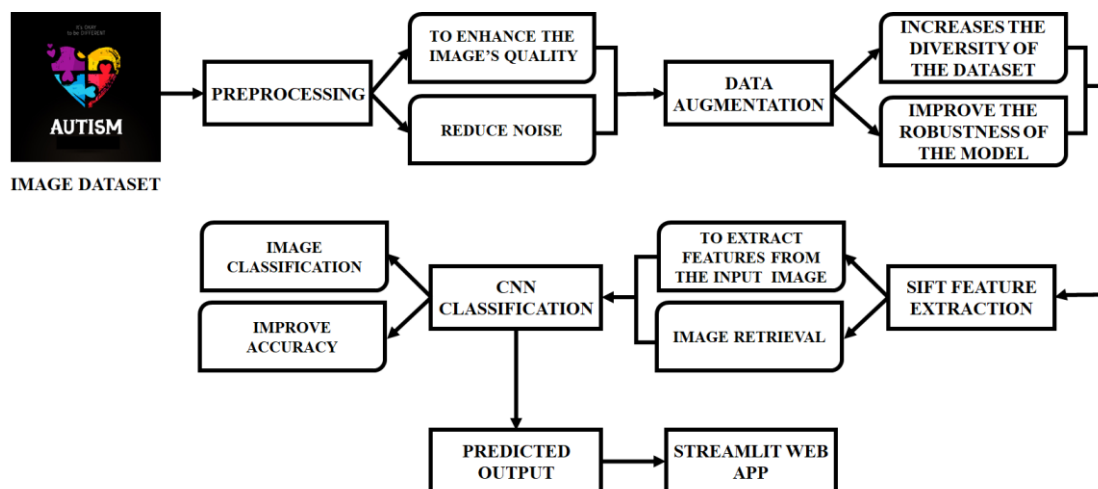


Figure 2Block Diagram of Proposed Work

In this system, convolutional neural networks (CNNs) are suggested for use in the diagnosis of autism spectrum disorder. Noise reduction and contrast enhancement are examples of preprocessing operations performed on the input picture to improve its quality. After the picture is preprocessed, data augmentation is used to increase the dataset's diversity and robustness for analysis. The scale-invariant feature transform (SIFT) is used for feature extraction after data augmentation. Regardless of changes in size, rotation, or illumination, this approach manages to capture distinct spots in the photos. To improve the CNN model's capacity to identify ASD-related patterns, these extracted characteristics are essential training inputs. An exceptionally accurate categorization of input pictures into ASD and non-ASD classes was the explicit goal of the CNN model's design and training. The CNN accomplishes remarkable results in detecting ASD-related traits in face pictures by means of an iterative procedure of model improvement and validation. Finally, the Streamlit web app incorporates the trained CNN model without any hitches, so users can see the results right in the app.

3.6 PREPROCESSING

When using Convolutional Neural Networks (CNNs) to identify ASD, preprocessing is an essential first step. Preprocessing is crucial for improving the efficacy of convolutional neural networks (CNNs) for autism spectrum disorder (ASD) diagnosis since the accuracy and usefulness of the input data are critical. Improving model performance and interpretability in ASD detection is the goal of preprocessing strategies, which seek to modify input data to better fit CNN needs. Data normalization, which entails uniformly scaling and distributing input information, is an important part of preprocessing. For the purpose of autism spectrum disorder (ASD) identification, this can include doing things like standardizing imaging data, such pixel intensities in face photographs or functional magnetic resonance imaging (fMRI) scans. Model convergence and generalization performance are both improved by normalization, which makes that the size and distribution of the input data are consistent.

Data augmentation, which includes applying modifications like scaling, rotation, and flipping to the original data in order to generate more training examples, is also an important preprocessing step. This method improves the CNN model's capacity to generalize to new data by increasing the variety and robustness of the training dataset, which decreases the likelihood of overfitting. When it comes to autism spectrum disorder (ASD) identification, data augmentation approaches may be used to enhance model performance by adding new inputs to the training dataset, such as face photographs and neuroimaging data. In order to extract useful features and decrease computing complexity, the preprocessing pipeline may also include dimensionality reduction and feature extraction methods. These methods enhance the performance and understandability of ASD detection models based on convolutional neural networks (CNNs) by locating important patterns and correlations in the input data and eliminating unnecessary or superfluous details. To improve the performance of the model and to optimize the input data for CNN-based ASD diagnosis, preprocessing is essential. This is because it allows for the extraction of important features that are relevant to the diagnostic job and helps to optimize the model overall. Clinicians and researchers may advance diagnostic capabilities and intervention options for people with



ASD by using proper preprocessing approaches to make CNN models for ASD detection more accurate, efficient, and interpretable.

3.7 DATA AUGMENTATION

Improving Convolutional Neural Networks (CNNs) for ASD identification relies heavily on data augmentation. The accessibility of varied and representative datasets is crucial for ASD diagnosis using CNNs. In order to make CNN models more resilient and better at detecting ASD, data augmentation methods try to diversify and expand the training dataset by creating synthetic versions of the original data. Data augmentation relies on generating more training examples by transforming the original data in various ways, including rotating, scaling, translating, and inverting. This includes applying these changes to several kinds of input data, such as neuroimaging data, behavioral recordings, and face photographs, in order to identify ASD. Data augmentation enhances the CNN model's diagnostic performance by reducing the likelihood of overfitting and increasing its generalizability to new data sets.

Adding random noise or perturbations to the input data is another way to supplement data. This makes the model more resilient to data artifacts and noise, and it mimics real-world unpredictability. Neuroimaging research has shown, for instance, that convolutional neural network (CNN) models may better identify ASD-related subtle patterns of brain activity when fMRI images include artificial noise. The CNN model may be trained with a diverse set of relevant features by using data augmentation approaches that are particular to the ASD population. These techniques can be adjusted to account for traits like behavioral reactions or variability in facial expressions. Because of this, the model is able to learn to distinguish between neurotypical controls and those with ASD, regardless of the input data's consistency. In order to make CNNs better at detecting ASD, data augmentation is essential. It does this by making the training dataset more diverse and resilient. Data augmentation, which involves creating artificial versions of the original data, improves the model's diagnostic performance and its capacity to generalize to new data, leading to more accurate and dependable techniques for detecting ASD.

3.8 FEATURE EXTRACTION

When using Convolutional Neural Networks (CNNs) to diagnose Autism Spectrum Disorder (ASD), feature extraction is an essential step. To diagnose autism spectrum disorder (ASD) using convolutional neural networks (CNNs), it is necessary to extract characteristics and patterns from input data that differentiate ASD patients from neurotypical controls. To help the CNN model learn discriminative features for reliable ASD detection, feature extraction approaches try to compress and make more useful the raw input data. Feature extraction in convolutional neural network (CNN)-based autism spectrum disorder (ASD) diagnosis often makes use of deep CNN architectures' hierarchical feature learning capabilities. In order to automatically learn hierarchical representations of input data at various levels of abstraction, deep convolutional neural networks (CNNs) use pooling and convolutional layers. For the purpose of autism spectrum disorder (ASD) identification, these acquired characteristics could map onto certain facial expressions, brain areas, or patterns of neural activity that are diagnostic of the disorder. In addition, when working with small amounts of training data, transfer learning is an effective method for feature extraction in CNN-based ASD identification. Using convolutional neural network (CNN) models that have already been trained on massive datasets for tasks like picture categorization is known as transfer learning. Researchers may take use of the information embodied in the pre-trained weights and fine-tune these models using ASD-specific data to extract high-level characteristics important to ASD identification. Facial pictures, behavioral recordings, and neuroimaging data are just a few examples of the input modalities that might benefit from domain-specific feature extraction methods. In facial image analysis, for instance, methods like texture analysis and face keypoint identification may be used to extract information pertaining to facial landmarks, emotions, and textures. In convolutional neural network (CNN)-based autism spectrum disorder (ASD) detection, feature extraction is essential because it promotes accurate classification by converting raw input data into a more discriminative representation. The CNN model's capacity to reliably and accurately diagnose ASD may be enhanced by combining deep convolutional neural network (CNN) architectures with transfer learning and domain-specific feature extraction methods. This allows researchers to efficiently extract important features from various input modalities.

4. RESULTS AND DISCUSSIONS

4.1PYTHON

This project's language of choice was Python. For many reasons, this was an easy choice to make. 1. The Python language is supported by a large community. A quick trip to Stack Overflow will fix any issue that may arise. Python is one of the most popular programming languages, therefore it's probable that any query you have will have a straightforward response.

Python offers a wide variety of robust tools that are well-suited for scientific computing. Popular and well-documented packages in Python include NumPy, Pandas, and SciPy. These packages modify the code needed to create a certain application and drastically reduce its size. This allows for rapid iteration.

3. The Python programming language is known for its flexibility and its ability to accommodate programs that mimic pseudocode. When it comes time to enforce and test the pseudocode provided in tutorial papers, this may be useful. When working with Python, this process can sometimes rather easy. But Python has its share of mistakes. Both the language and its packages are known for its dynamic writing and Duck writing, respectively. For example, if a package method returns something that seems to be an array but is really not an array, this could be annoying. There is a lot of room for trial and error testing in Python since the standard documentation does not explicitly identify the return type of a method. This is in contrast to languages that are well-written.

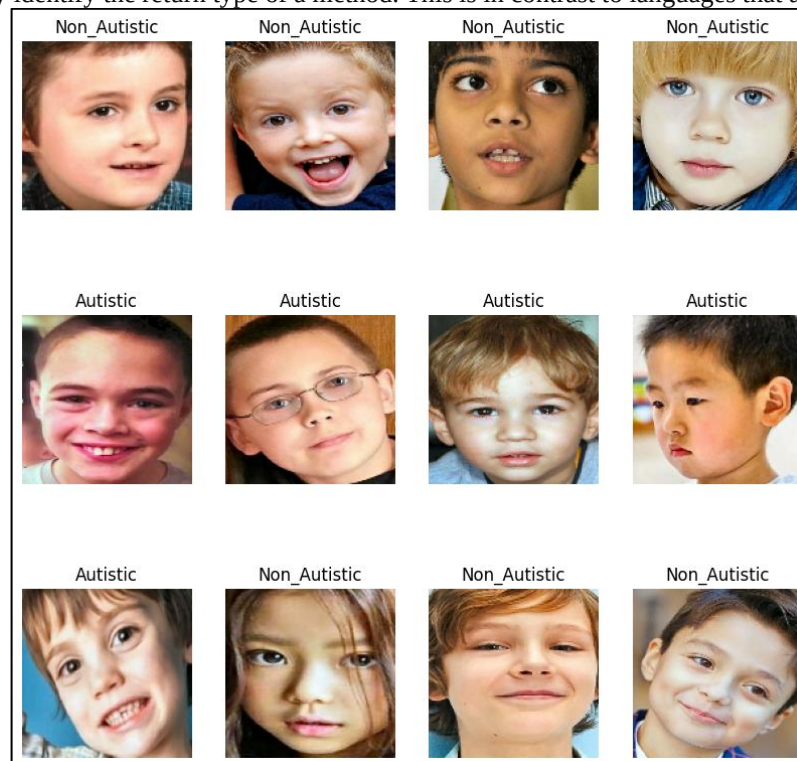


Figure 3Input Image

Figure 3 represents the input image. In this image autism and non-autism disorder is presented. Then the input image is moved to the further process

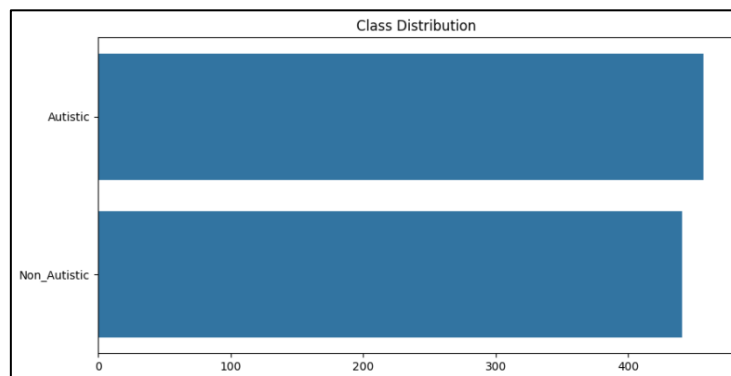
**Figure 4** Class Distribution

Figure 4 shows the class distribution. The spread of data across different categories or classes within a dataset, crucial for understanding the balance or imbalance among various groups.

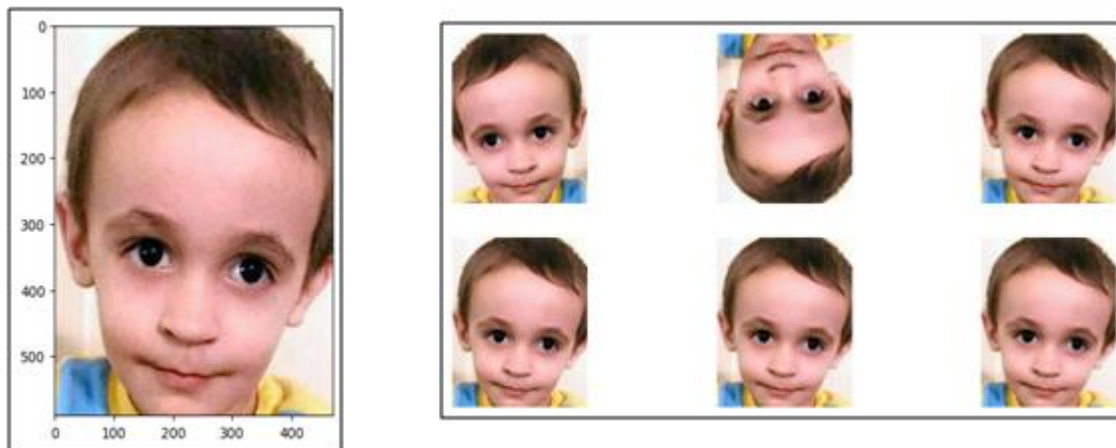
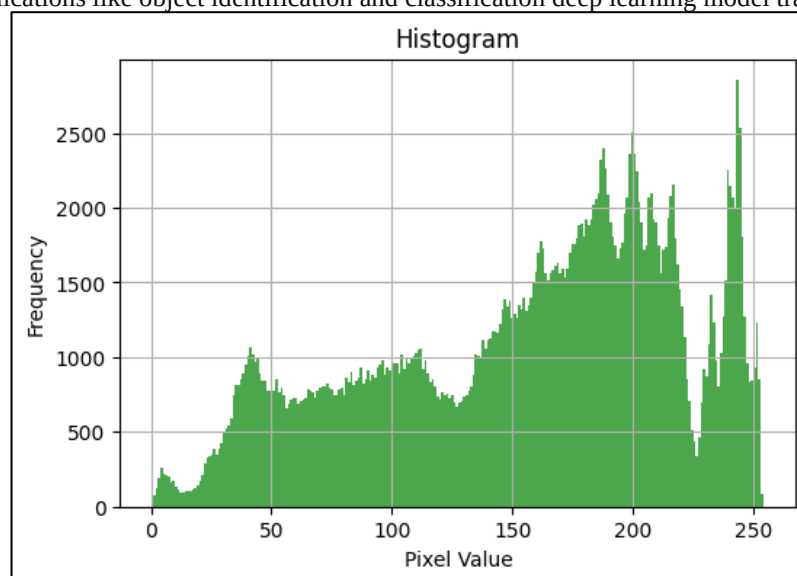
**Figure 5** Image Augmentation

Figure 5 shows the augmented image. Improving model robustness and generalization, it enriches datasets by performing modifications like flipping, scaling, and rotation to diversify pictures. Essential for computer vision applications like object identification and classification deep learning model training.

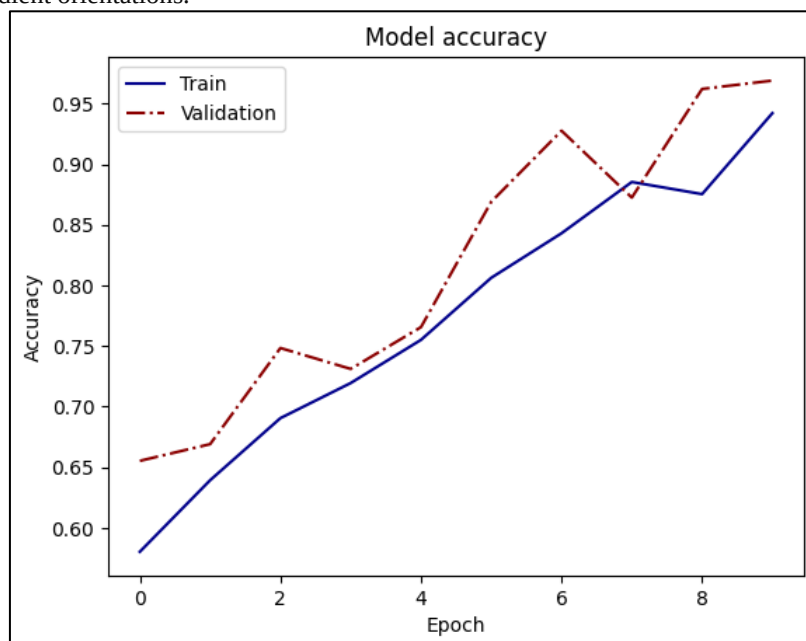
**Figure 6** Histogram

The histogram is shown in Figure 6. It uses intervals or bins to divide numerical data and bars of varied heights to illustrate the frequency of values inside each bin, displaying the distribution of the data. You can see the distribution of the data graphically, which is useful for finding trends or unusual occurrences.



Figure7Sift Feature Extraction

Figure 7 shows the Sift Feature Extraction. It identifies keypoints in an image and describes them using histograms of gradient orientations.



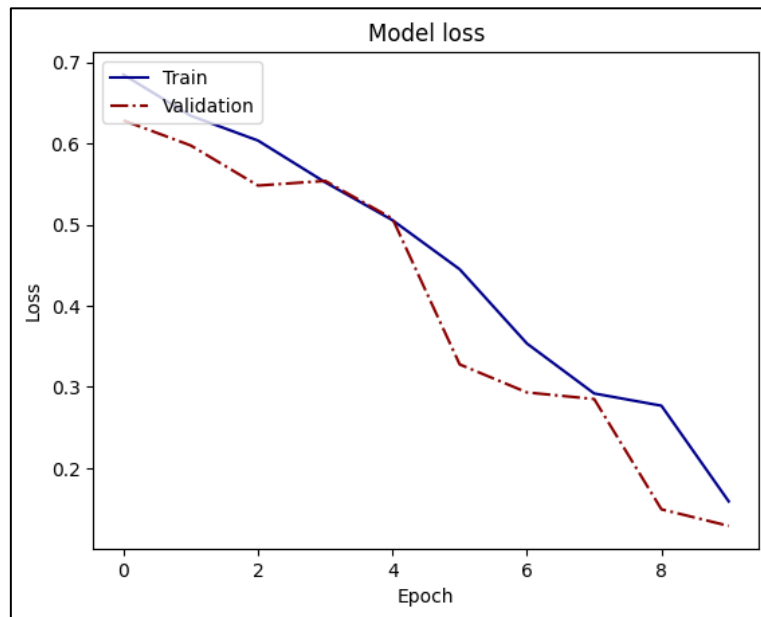
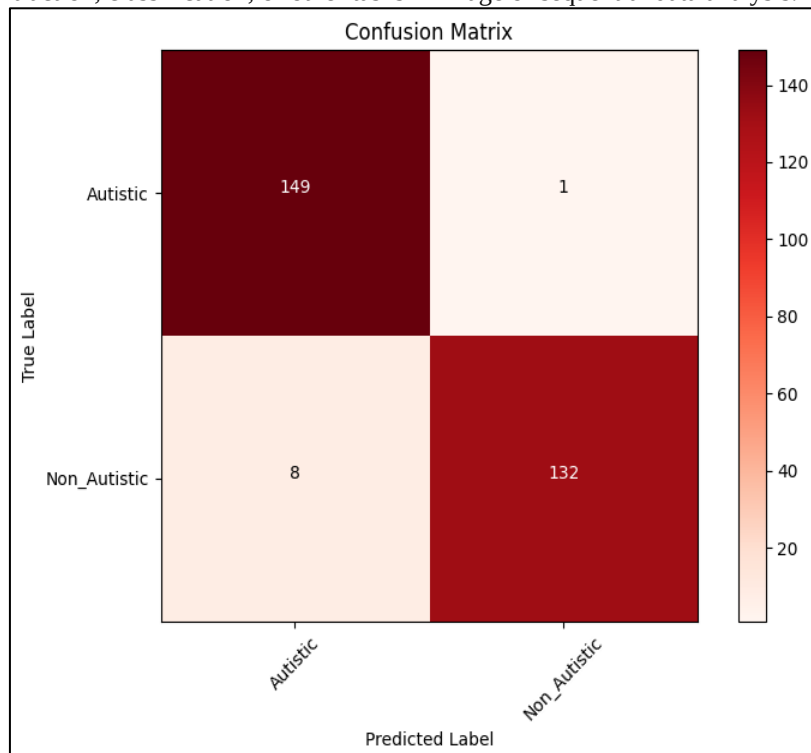


Figure 8Modified CNN

Figure 8 shows the modified CNN. It adapts traditional CNN structures with innovative techniques to enhance feature extraction, classification, or other tasks in image or sequential data analysis.



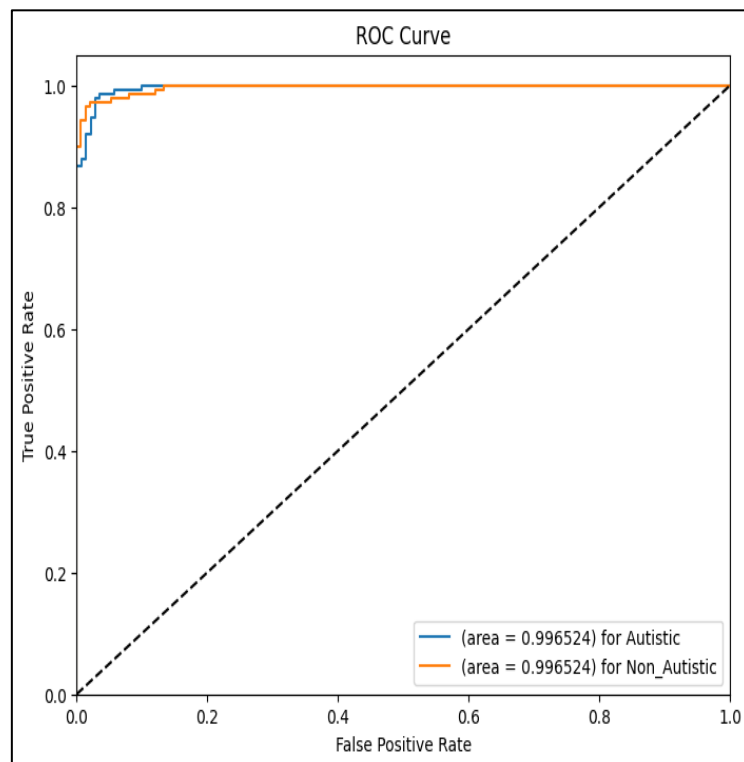
**Figure 9** Confusion Matrix

Figure 9 represents the Confusion Matrix. That provides a summary of the performance of a classification algorithm by displaying the counts of true positives, false positives, true negatives, and false negatives.

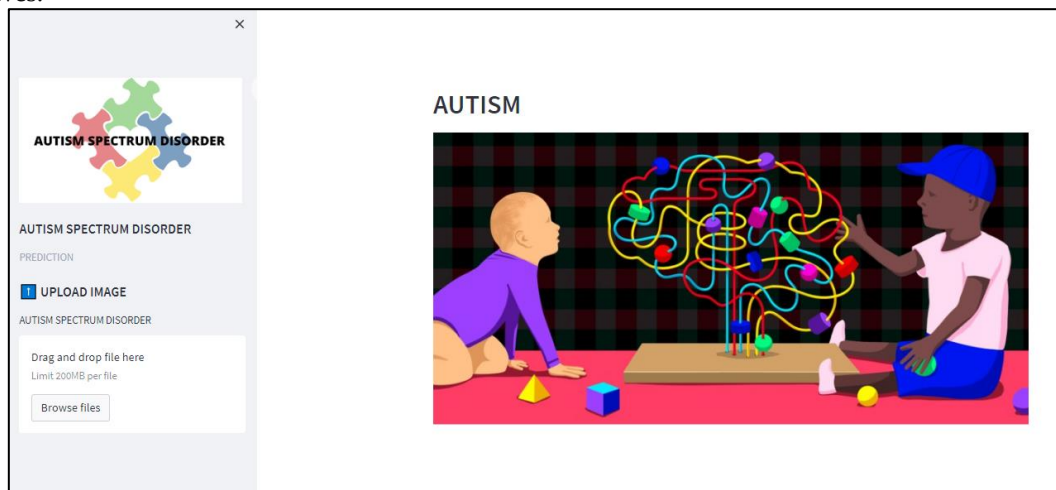
**Figure 10** Upload Image

Figure 10 shows the Upload Image. Uploads and enhances images, ensuring optimal quality and efficiency.

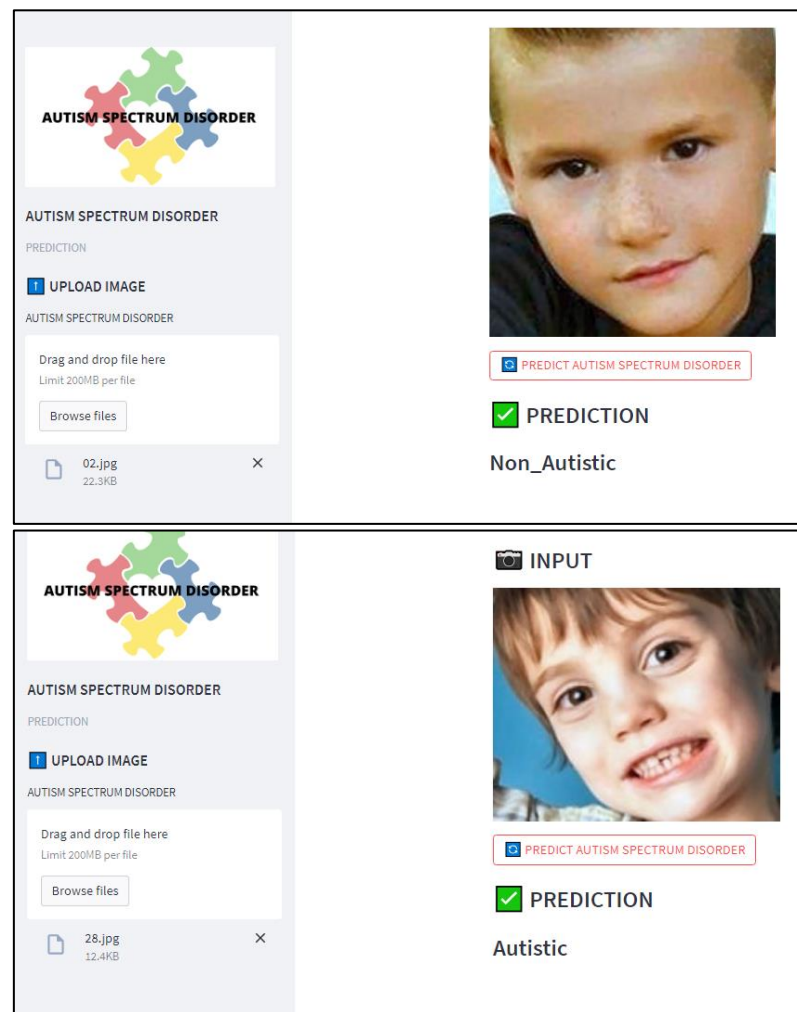
**Figure11** Predicted Output

Figure 11 indicates the Predicted Output. Encapsulates the transformed representation of input imagery, reflecting the model's applied enhancements, classifications, or modifications

CONCLUSION

The goal of this research was to provide a thorough method for detecting autism spectrum disorder via the use of Streamlit web application and Convolutional Neural Networks (CNNs). Picture pre-processing for quality improvement, data supplementation for dataset variety, and feature extraction utilizing the scale-invariant feature transform (SIFT) are all essential elements in the process. The CNN model relies on these extracted characteristics to train itself to correctly distinguish between ASD and non-ASD input pictures. High accuracy in recognizing ASD-related characteristics from face photos is achieved by the CNN via an iterative process of model improvement and validation. In addition, the trained CNN model is easily integrated into the Streamlit web application, which improves usability and accessibility for users. This connection allows users to observe the output in real-time inside the app interface. In sum, this project is a huge step forward in the field of autism spectrum disorder (ASD) early detection and assessment using cutting-edge tech. It provides a non-invasive, efficient, and user-friendly solution for researchers, clinicians, and people in need of help.



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