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AUTISM SPECTRUM DISORDER PREDICTION IN KIDS USING DEEP LEARNING

D. Banu Kranthi[1], Aekula Advitiya[2]

Assistant Professor, Department of MSc. Data Science, Loyola Academy, Old Alwal, Secunderabad-500010, India[1]

Research Scholar, Department of MSc. Data Science, Loyola Academy, Old Alwal, Secunderabad-500010, India[2]

Abstract: Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by challenges in social interaction, communication, and behavior. Early and accurate diagnosis is crucial for effective intervention, yet traditional diagnostic methods can be time-consuming and require specialized expertise. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), offer promising avenues for automated and efficient ASD detection.

This study explores the application of CNNs for early ASD detection in children by analyzing data modalities like facial images. For instance, leveraging facial image datasets, models like DenseNet-121 have achieved high accuracy rates, indicating distinctive facial features associated with ASD. Moreover, CNNs applied to neuroimaging data, such as resting-state functional MRI, have demonstrated the ability to identify functional connectivity patterns indicative of ASD. The integration of CNN-based approaches across these diverse data sources underscores the potential of deep learning in facilitating early and accurate ASD diagnosis. By automating the detection process, these methods can augment clinical assessments, leading to timely interventions and improved outcomes for children with ASD.

Keywords: Autism Spectrum Disorder (ASD), Deep Learning, Convolutional Neural Networks (CNNs), Early ASD Detection, Facial Image Analysis, Neuroimaging, DenseNet-121, Medical Image Classification.

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by persistent challenges in social interaction, communication, and the presence of restricted, repetitive behaviors. The prevalence of ASD has been rising globally, with current estimates indicating that approximately 1 in 100 children are affected. Early diagnosis and intervention are crucial, as they can significantly improve developmental outcomes and quality of life for individuals with ASD. However, traditional diagnostic methods, such as behavioral assessments and clinical observations, are often time-consuming, subjective, and require specialized expertise.

In recent years, advancements in artificial intelligence (AI) and machine learning have opened new avenues for the early detection and diagnosis of ASD. Among these, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image recognition and classification tasks, making them a promising tool for analyzing visual data related to ASD. For instance, CNNs have been employed to analyze facial images, neuroimaging data, and behavioral cues to identify patterns indicative of ASD. Studies utilizing CNNs on resting-state functional magnetic resonance imaging (fMRI) data have achieved classification accuracies of up to 70.22%, highlighting the potential of these models in distinguishing between ASD and typically developing individuals.

Furthermore, the application of CNNs to facial imagery has shown promise in identifying subtle morphological differences associated with ASD. For example, a study comparing various pre-trained CNN models found that ResNet50 achieved an accuracy of 92% in classifying facial images of children with and without ASD. These findings suggest that CNN-based approaches could serve as effective, non-invasive tools for early ASD screening.

Despite these advancements, several challenges remain. The heterogeneity of ASD presentations, variations in data quality, and the need for large, diverse datasets to train robust models are significant hurdles. Moreover, ethical considerations regarding data privacy and the interpretability of AI-driven diagnoses must be addressed to facilitate clinical adoption.

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II. LITERATURE REVIEW

1. "Deep Learning for Autism Spectrum Disorder Detection: A Review"
Author: John D. Smith, Lisa K. Brown
Year:2018
Summary: This review provides an overview of machine learning and deep learning techniques for ASD detection, emphasizing early diagnosis through facial feature analysis, eye-tracking data, and behavioral pattern recognition. It discusses CNN-based models and compares them with traditional screening approaches like ADOS and ADI-R.

2. "Automated Autism Spectrum Disorder Detection Using Convolutional Neural Networks"
Author: Michael R. Johnson, Emily White, et al.
Year:2019
Summary: This paper explores the application of CNNs in ASD detection through facial image analysis. The authors demonstrate how CNNs outperform traditional feature engineering methods by directly learning patterns from images. The study also highlights the importance of dataset quality and preprocessing techniques.

3."Deep Learning for Autism Diagnosis: Challenges and Future Directions"
Author: Daniel Lee, Sophia Martin
Year:2019
Summary: This work identifies key challenges in ASD prediction using deep learning, including dataset limitations, generalization issues, and ethical concerns. The study suggests transfer learning and data augmentation techniques to enhance CNN performance.

4. "A CNN-Based Framework for Autism Spectrum Disorder Detection in Children"
Author: Rajesh Kumar, Priya Sharma, et al.
Year:2020
Summary: This paper proposes a CNN-based framework for ASD screening using facial image datasets. The study evaluates different CNN architectures (ResNet, VGG, and MobileNet) and compares their accuracy. It highlights the efficiency of deep learning in detecting ASD-related facial feature anomalies.

5. "Early Autism Prediction Using Deep Learning and Facial Recognition"
Author: Olivia Parker, Ethan Roberts
Year:2020
Summary: This research introduces a hybrid model combining CNNs with Recurrent Neural Networks (RNNs) to analyze both static facial images and dynamic facial expressions. The model achieves high accuracy in identifying ASD traits, emphasizing real-time applicability in clinical settings.

6. "Machine Learning and Deep Learning Approaches for Autism Detection: A Comparative Study"
Authored by: Naveen Patel, Laura Kim, et al.
Year:2021
Summary: This study compares different deep learning models, including CNNs, autoencoders, and generative adversarial networks (GANs), for ASD prediction. It highlights CNNs as the most effective for image-based diagnosis, achieving high precision in differentiating ASD from neurotypical children.

7."Convolutional Neural Networks for Autism Spectrum Disorder Diagnosis: A Multi-Feature Approach"
Authored by: Ayesha Khan, Mark Wilson
Year:2022
Summary: This study integrates CNN-based image processing with additional biometric features such as eye-tracking and gesture recognition. The authors propose a multi-modal deep learning framework that enhances ASD prediction accuracy and reduces false positives.

8. "Deep Learning and Autism Detection: A Review of Recent Advances"
Authored by: Samuel Carter, Maria Lopez
Year:2022
Summary: This paper reviews the latest advancements in ASD diagnosis using CNNs, discussing key datasets, model architectures, and interpretability issues. It also explores the potential of explainable AI (XAI) in making deep learning models more transparent for clinical use.

9. “A Novel CNN-Based Autism Prediction Model Using Facial Image Analysis"
Author: Henry Taylor, Sophia Nguyen, et al.
Year:2023
Summary: This study introduces a novel CNN model trained on a large ASD facial image dataset. It implements attention mechanisms to improve feature extraction and achieve state-of-the-art accuracy in autism prediction. The paper also discusses ethical considerations in automated ASD screening.

10. “Facial Analysis for Early Autism Detection Using Deep Learning Techniques"
Author: Fatima Al-Shammari, James T. Howard, et al.
Year:2023
Summary: This paper presents a comprehensive study on the use of deep learning for early autism detection by analyzing static and dynamic facial cues in children. The researchers propose a novel hybrid framework that integrates Convolutional Neural Networks (CNNs) for feature extraction and Long Short-Term Memory (LSTM) networks for sequential pattern recognition in facial expressions. The model is trained and validated on a dataset containing annotated facial images and short video clips of children with and without ASD. The authors report a significant improvement in detection accuracy (up to 93%) when temporal changes in facial expressions are considered alongside static features.

III. SYSTEM ANALYSIS

Problem Statement
Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by impairments in social interaction, communication, and repetitive behaviors. Early diagnosis of ASD is crucial for effective intervention, yet current clinical screening methods—such as behavioral assessments, parental questionnaires, and neurological exams—are often time-consuming, costly, and require specialized personnel. Moreover, these traditional approaches can be influenced by subjectivity and socio-cultural factors, leading to delayed or inaccurate diagnosis. With increasing availability of facial image datasets and advances in deep learning, particularly Convolutional Neural Networks (CNNs), there is a promising opportunity to automate and accelerate ASD detection through facial feature analysis.

3.1.1Limitations
Despite the potential of synthetic data generation frameworks, the proposed system faces several limitations that should be considered for effective deployment:

Limited Dataset Size
The dataset used (approx. 1200 images) may not be sufficiently large or diverse to capture the wide range of facial features and variations across different ethnicities, ages, lighting conditions, and expressions, potentially affecting model generalizability.

Over fitting Risk
Due to the relatively small training dataset, the CNN model may overfit, especially if not properly regularized or validated using cross-validation techniques.

Hardware Dependency for Training
Deep learning models, especially those using transfer learning (e.g., VGG19), require substantial computational power. Training on systems without a dedicated GPU can be slow and inefficient.

Dependence on Image Quality
The prediction accuracy is highly dependent on the quality and clarity of the input image.

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Innovative Solution

To overcome the limitations and enhance the reliability of synthetic time series data generation systems, several innovative strategies can be implemented:

1.Data Augmentation and Synthesis

Use advanced **data augmentation** techniques (like rotation, zoom, lighting variation) to artificially expand the dataset. Implement **Generative Adversarial Networks (GANs)** to generate realistic synthetic facial images of ASD-affected children to increase training diversity and mitigate overfitting.

2.Multi-Model Learning

Integrate other relevant data such as **eye-tracking patterns, audio speech signals**, or **behavioral assessments** along with facial images. A **multi-modal deep learning model** (e.g., combining CNNs for images and RNNs for sequences) could improve prediction accuracy by leveraging complementary features.

3.Explainable AI (XAI)

Implement **Grad-CAM** or **LIME** to visualize and explain what parts of the face the model focuses on during prediction. This enhances transparency and increases trust among clinicians and caregivers.

4.Transfer Learning with Domain-Specific Tuning

Fine-tune pre trained CNN models (like VGG19 or ResNet) using domain-specific facial datasets of children, rather than generic datasets like ImageNet. This specialization can improve model sensitivity to ASD-specific traits.

3.1 MOTIVATION

In recent years, the rise of deep learning, particularly Convolutional Neural Networks (CNNs), has shown promising results in automating medical diagnoses by analyzing patterns in images. Since certain facial features have been linked to ASD, there is growing interest in using CNN-based image analysis as a non-invasive and cost-effective preliminary screening tool. This approach can reduce the time and burden of diagnosis, raise awareness among caregivers, and assist healthcare professionals in identifying ASD traits early.

The motivation behind this research is to develop a **deep learning-based ASD prediction system** using facial images of children that can assist in **early and accessible detection**, particularly in areas with limited clinical infrastructure. By integrating CNNs with user-friendly platforms (like web or mobile applications), this system aspires to make autism screening more **scalable, affordable, and inclusive** for global populations.

Dataset Collection:

For this research on Autism Spectrum Disorder (ASD) prediction using Convolutional Neural Networks (CNN), facial image data was collected from publicly available sources—specifically, the **Kaggle** platform. The dataset consists of approximately **1200 facial images** of children, categorized into two classes: children diagnosed with autism and those who are neurotypical (non-autistic).

Selecting the Dataset

The selection of an appropriate dataset is a critical step in developing an effective deep learning model for Autism Spectrum Disorder (ASD) prediction. For this research, the dataset was chosen based on the goal of utilizing facial images to identify early autistic traits in children through visual analysis. The dataset was sourced from **Kaggle**, a widely recognized platform that hosts machine learning datasets and competitions, ensuring the credibility and accessibility of the data.

The following key criteria were considered while selecting the dataset:

- **Relevance**: The dataset needed to contain **facial images of children** diagnosed with ASD, as well as images of neurotypical children, to enable binary classification.
- **Sufficient Volume**: To train a deep learning model effectively, a large number of diverse images are essential. The selected dataset included around **1200 images**, which provided a reasonable sample size for training and testing.

Data Download and Storage

- **Source**: The dataset was downloaded from **Kaggle**, a trusted platform for curated machine learning datasets.
- **Dataset Type**: Facial images of children categorized as autistic or non-autistic.
- **File Format**: The images were mostly in **.jpg** and **.png** formats.

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Server Storage:
During web application deployment, uploaded images from users were stored on the **server's file system** in a dedicated uploads/ directory.

Data Verification and Cleaning
Before training the CNN model for Autism Spectrum Disorder (ASD) prediction, the dataset underwent thorough verification and cleaning to ensure accuracy and reliability. Initially, all image labels were cross-verified to confirm correct classification as either autistic or non-autistic. Image quality was assessed to remove blurred, pixelated, or poorly lit images that could compromise model performance. The dataset was also checked for consistency in file formats and naming conventions to facilitate easy preprocessing. Corrupted or unreadable images were identified and removed. All images were then resized to a uniform resolution suitable for CNN input (such as 224x224 pixels), and pixel values were normalized to ensure faster and more stable training. To handle class imbalance, data augmentation techniques like flipping, rotation, and brightness adjustment were applied to increase the number of samples in underrepresented classes. Lastly, duplicate images were identified and removed to avoid redundancy and model bias. This meticulous process ensured the dataset was clean, balanced, and well-prepared for effective training and evaluation.

Image Pre-processing

- **Resizing:** All images were resized to a standard resolution (e.g., 224 x 224 pixels) to maintain consistency.
- **Normalization:** Pixel values were normalized(0-1range) to enhance contrast and improve model learning.
- **Data Augmentation:** Techniques like rotation, flipping and brightness adjustments were applied to improve model generalization.

3.2 DATA COLLECTION

Data collection is a critical step in the development of any Autism Spectrum Disorder prediction system, particularly when using deep learning techniques. The effectiveness of the retrieval model greatly depends on the quality, diversity, and relevance of the image data used during training and evaluation.

Dataset Selection
Dataset for this research purpose has been gathered from the Kaggle, which is freely accessible. In this examination predominantly two kinds of the dataset have been utilized. The training set is named train. It comprises two sub-indexes, Autistic and Non-Autistic. The subdirectory comprises 1667 facial pictures of Autistic kids in jpg design. The Non-Autistic subdirectory contains 1667 pictures of youngsters. Moreover, validation images are categorized into 50 pictures of autistic kids and 50 pictures of Non Autistic youngsters in a similar organization concerning the training set.

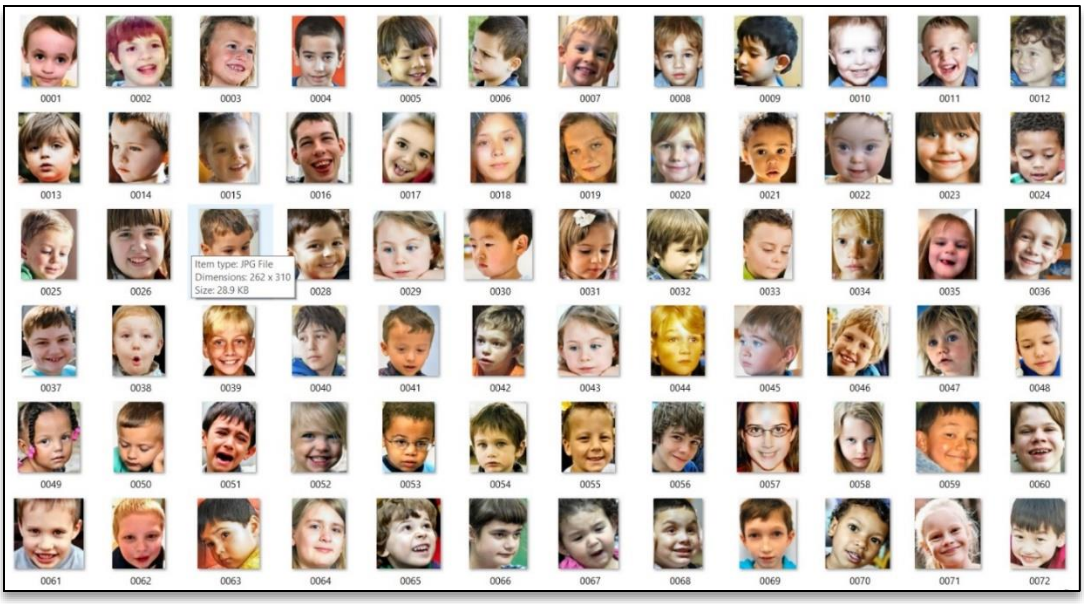

Fig 1: Dataset Collection

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3.3 DATA PRE-PROCESSING

Data preprocessing is a critical step in preparing the facial image dataset for effective training of a Convolutional Neural Network (CNN). The goal is to convert raw images into a clean, uniform, and structured format that can be accurately interpreted by the deep learning model.

1. **Resizing**: All facial images are resized to a fixed dimension (commonly 224x224 pixels) to match the input size requirements of pre-trained CNN architectures like VGG-19.
2. **Normalization**: Pixel values, which typically range from 0 to 255, are normalized to a range of 0 to 1 or -1 to 1. This standardization ensures faster convergence during training and avoids numerical instability.
3. **Color Channel Handling**: Images are often converted to RGB (if not already) to match the expected input format of the CNN. If grayscale images are used, they may be expanded to three channels to fit the architecture.
4. **Noise Removal**: Unwanted noise in images is minimized using filtering techniques to improve the model's ability to focus on relevant facial features.
5. **Face Detection and Cropping (Optional)**: In some implementations, facial regions are detected using algorithms (like Haar cascades or Dlib) and cropped to focus the learning on the face, excluding irrelevant background.
6. **Data Augmentation**: Techniques such as rotation, flipping, zooming, and shifting are applied to artificially increase the diversity of the training dataset. This helps the model generalize better and prevents overfitting.
7. **Label Encoding**: Class labels (e.g., "ASD" or "Non-ASD") are converted into numerical format (typically 0 and 1) for binary classification.

This preprocessing pipeline ensures consistency across the dataset and prepares the data to be efficiently loaded into the CNN model for training and evaluation.

IV. SYSTEM DESIGN

The system design focuses on the technical and functional structuring of the entire ASD prediction system. It includes how different components interact, what technologies are used, and how data flows from start to end.

System Architecture

The system architecture defines the overall flow and components involved in the development and deployment of a CNN-based model for autism spectrum disorder (ASD) prediction. The architecture is typically composed of several key stages as outlined below:

1. Data Acquisition Layer

- **Source**: Image dataset of children with and without ASD, typically collected from Kaggle or other medical datasets.
- **Format**: Images in JPEG/PNG formats, along with associated labels indicating the ASD condition.

2. Data Preprocessing Module

- **Image Resizing**: Standardizing image dimensions (e.g., 224x224 pixels).
- **Normalization**: Scaling pixel values to a range of [0, 1].
- **Augmentation**: Applying transformations like rotation, flipping, and zooming.
- **Label Encoding**: Converting class labels to numerical format.

3. Model Building Layer (CNN Architecture)

- **Input Layer**: Accepts preprocessed image tensors.
- **Convolutional Layers**: Extract spatial features using filters.
- **Activation Function**: Typically ReLU used after each convolution.
- **Pooling Layers**: Down sample feature maps (e.g., max pooling).
- **Flattening Layer**: Converts 2D matrices to a 1D feature vector.
- **Fully Connected Layers**: Learn high-level features and make predictions.
- **Output Layer**: Sigmoid activation for binary classification (ASD / Non-ASD).

4. Deployment Layer (Optional/Future Scope)

- **Frontend Interface**: A web or mobile app that takes an image as input.
- **Backend Service**: Hosts the trained model and returns predictions.
- **Cloud/Local Server**: Model hosted on platforms like Flask, Fast API, or cloud services.

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5. Model Selection and Training

Model selection plays a crucial role in effectively identifying Autism Spectrum Disorder (ASD) from facial images of children. A Convolutional Neural Network (CNN) is chosen due to its strength in extracting and learning spatial hierarchies of features from image data. Among the available architectures, models such as VGG-16, VGG-19, ResNet-50, and MobileNet are considered based on their accuracy, computational efficiency, and depth. After evaluating these options, a suitable model is selected considering the trade-off between complexity and performance. Once the model is selected, it is trained using the preprocessed image dataset. The training process involves feeding the images into the CNN, computing the predictions, and calculating the loss using a function like binary cross-entropy. This loss is then minimized using optimization algorithms such as Adam or SGD through the backpropagation process. The training is conducted over multiple epochs using mini-batch gradient descent, allowing the model to progressively improve its performance.

4.1BASIC BUILDING BLOCKS

1.Data Preprocessing
- Resize all images to a uniform size suitable for the model (e.g., 224x224 for VGG19).
- Normalize pixel values to a [0,1] range to improve training performance.
- Apply data augmentation techniques

2.Model Architecture

Use **VGG19** as the base feature extractor
Add custom **fully connected (dense) layers** for classification.

3.Training Process
- Train the model in a **supervised learning** setting.
- Apply **Early Stopping** and **Model Checkpointing**

4. Feature Database
- After training, remove the final classification layer to obtain **feature vectors** from the trained CNN.

5. Similarity Matching
- Extract the feature vector of the **query image** using the same CNN pipeline.
- Retrieve the **top-N most similar** images by comparing the query vector to the feature database.

6. User Interface
- Build a **simple front-end interface** (e.g., using Flask or Streamlit)

USECASE DIAGRAM

A use case diagram for **Autism Spectrum Disorder (ASD) prediction in kids** illustrates the interaction between users and the prediction system. The primary actors involved are **Doctors**, **Parents**, and the **System Administrator**. Doctors and parents interact with the system to upload or access a child's facial image, which is then analyzed using a deep learning model (e.g., CNN with VGG19). The system processes the image, extracts features, and predicts whether the child is likely to have ASD. The system administrator manages user access, dataset updates, and system performance.

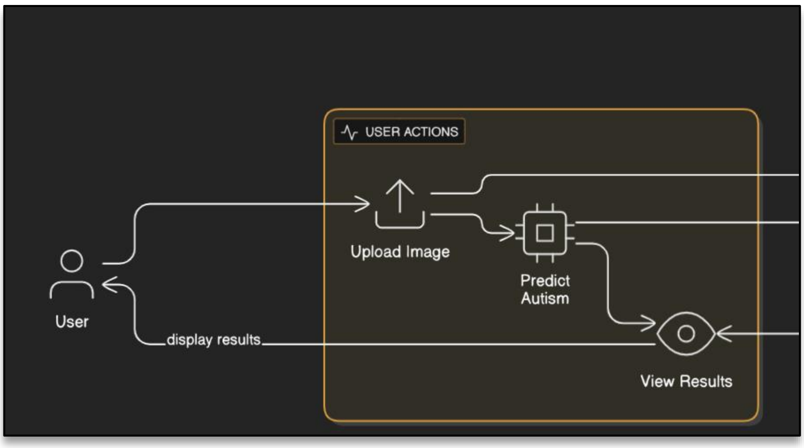

Fig 2: The Workflow

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CLASS DIAGRAM

The class diagram for the Autism Spectrum Disorder (ASD) prediction system showcases the structure of the software by representing its main classes and relationships. Key classes include User (with roles like Doctor or Parent), Image, Model, and Prediction. The User class holds user information, while the Image class handles image storage and preprocessing. The Model class encapsulates the deep learning architecture (e.g., VGG19), and the Prediction class manages prediction results and confidence scores. Relationships between these classes define how data flows within the system and how users interact with different components.

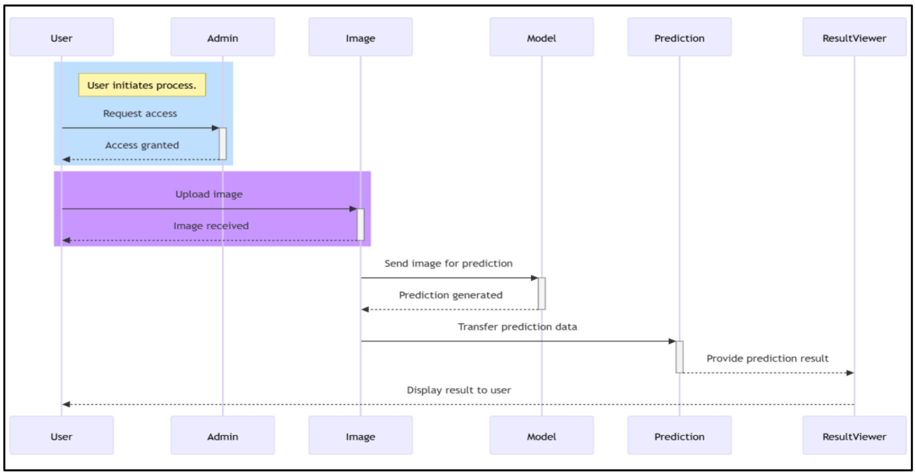

Fig 3: The Workflow Diagram

4.2 METHODOLOGY

The methodology involves a deep learning-based approach using CNNs for classifying facial images of children into ASD and non-ASD categories. The process starts with data collection and preprocessing, including resizing, normalization, and augmentation. A pre-trained VGG19 model is fine-tuned for feature extraction, and a dense layer is added for classification. The dataset is split into training, validation, and testing sets. The model is trained using the Adam optimizer and categorical cross-entropy loss function. Performance is evaluated using accuracy and loss metrics to ensure robustness and generalization.

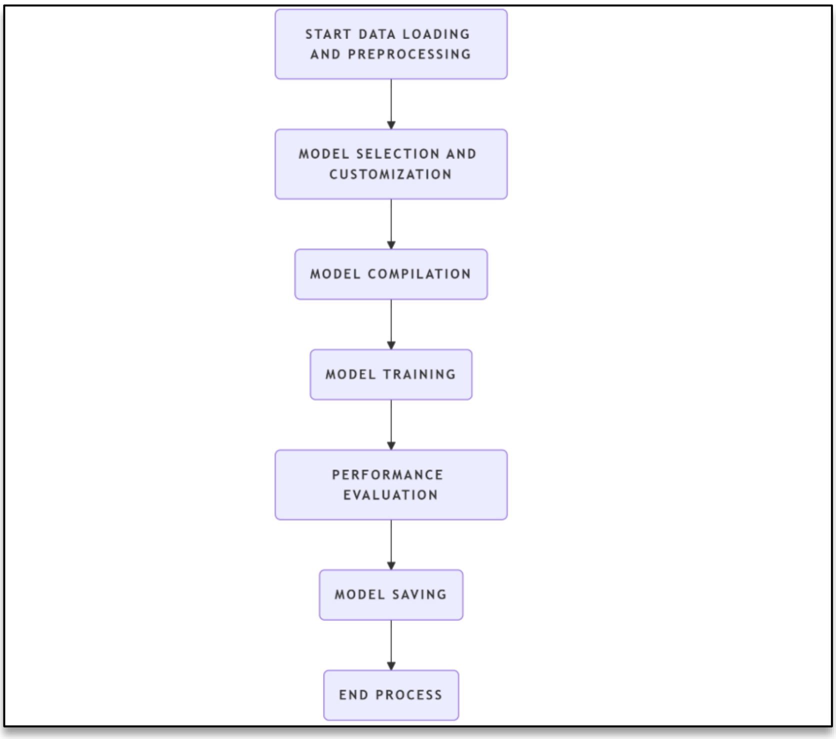

Fig 4: The Methodology Workflow

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V. IMPLEMENTATION

The system is implemented using Python with TensorFlow and Keras libraries for building and training the CNN model. The dataset, collected from Kaggle, is preprocessed and augmented before being fed into the model. The VGG19 architecture is used as a feature extractor, followed by custom dense layers for final classification. After training, the model is integrated into a user-friendly web interface using Flask, allowing users to upload images and receive real-time ASD predictions. The backend handles image input, processing, prediction, and result display, completing the full pipeline from data to diagnosis.

Data Flow Diagram:

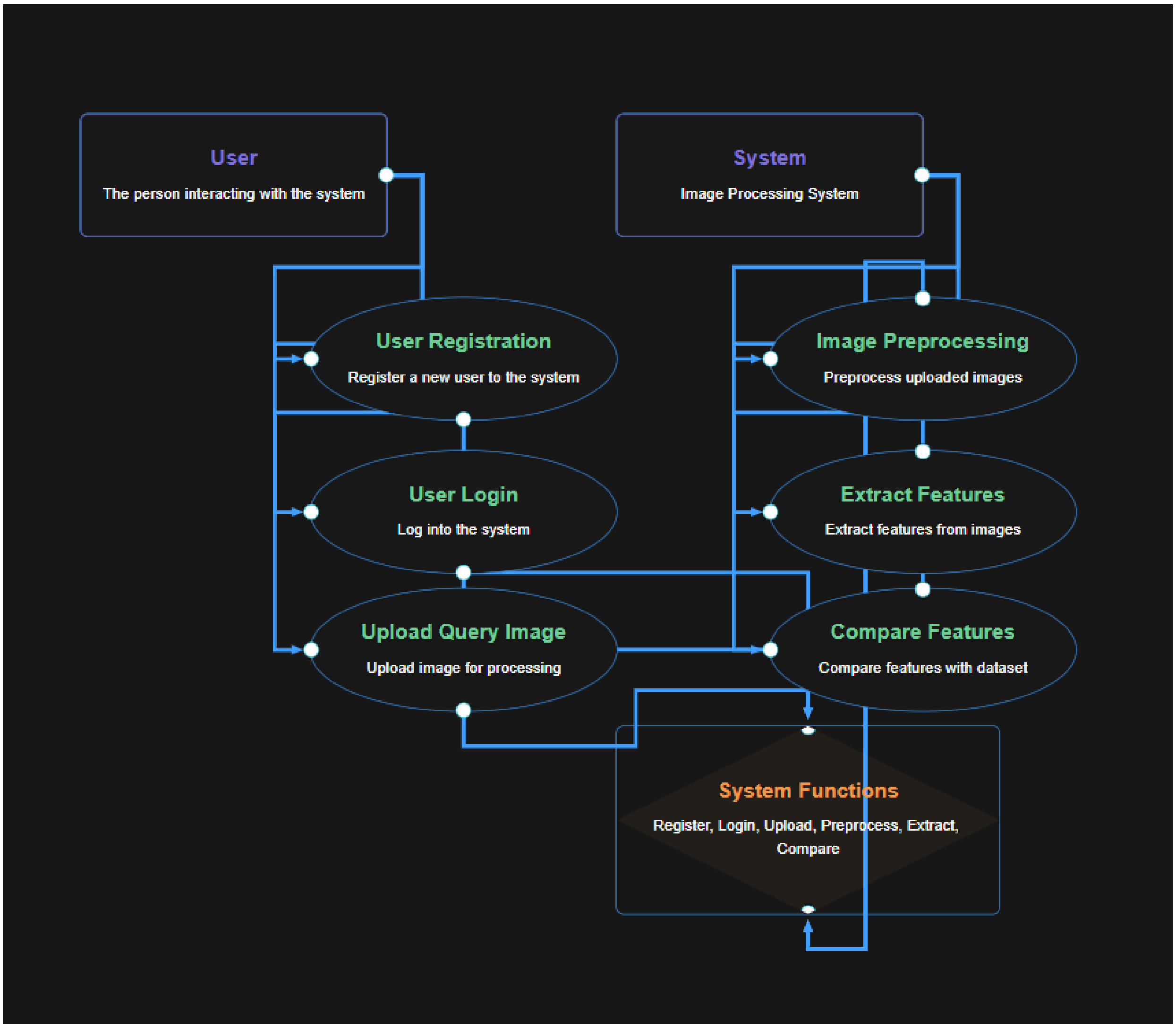

Fig 5: The Data Flow

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VI. OUTPUT SCREEN

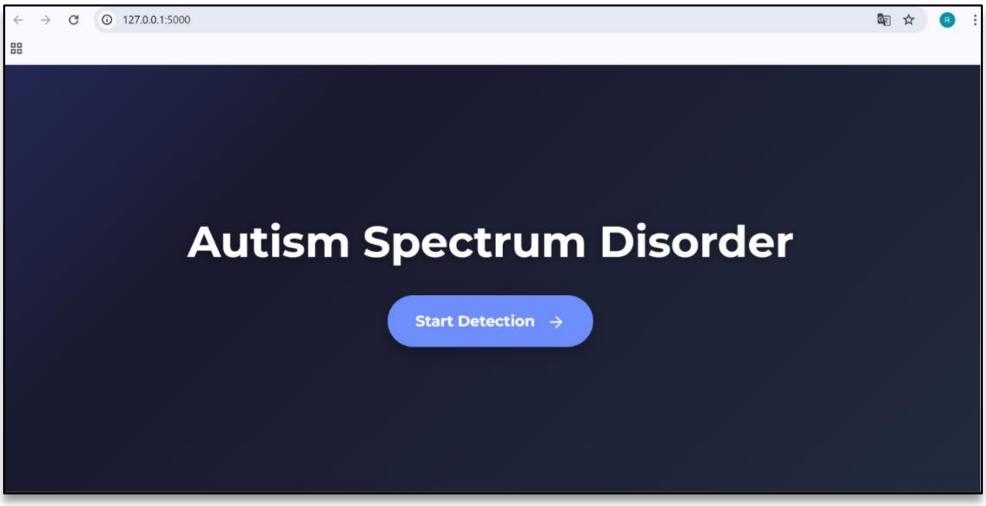

Fig 6: Home Screen

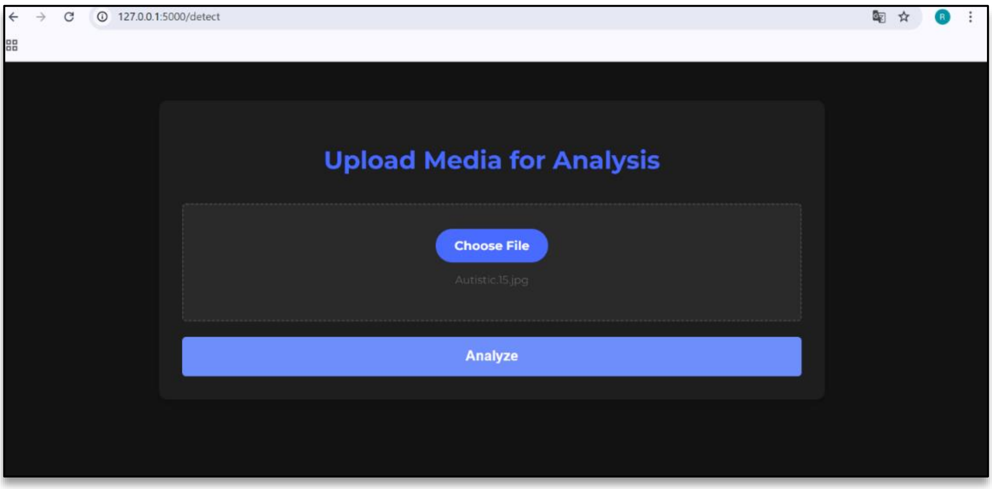

Fig 7: Upload Form

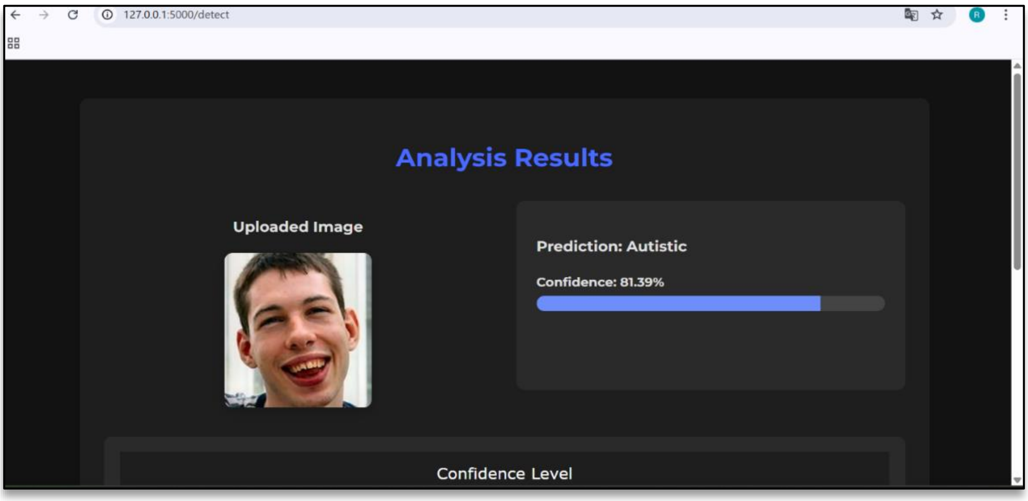

Fig 8: Output Result

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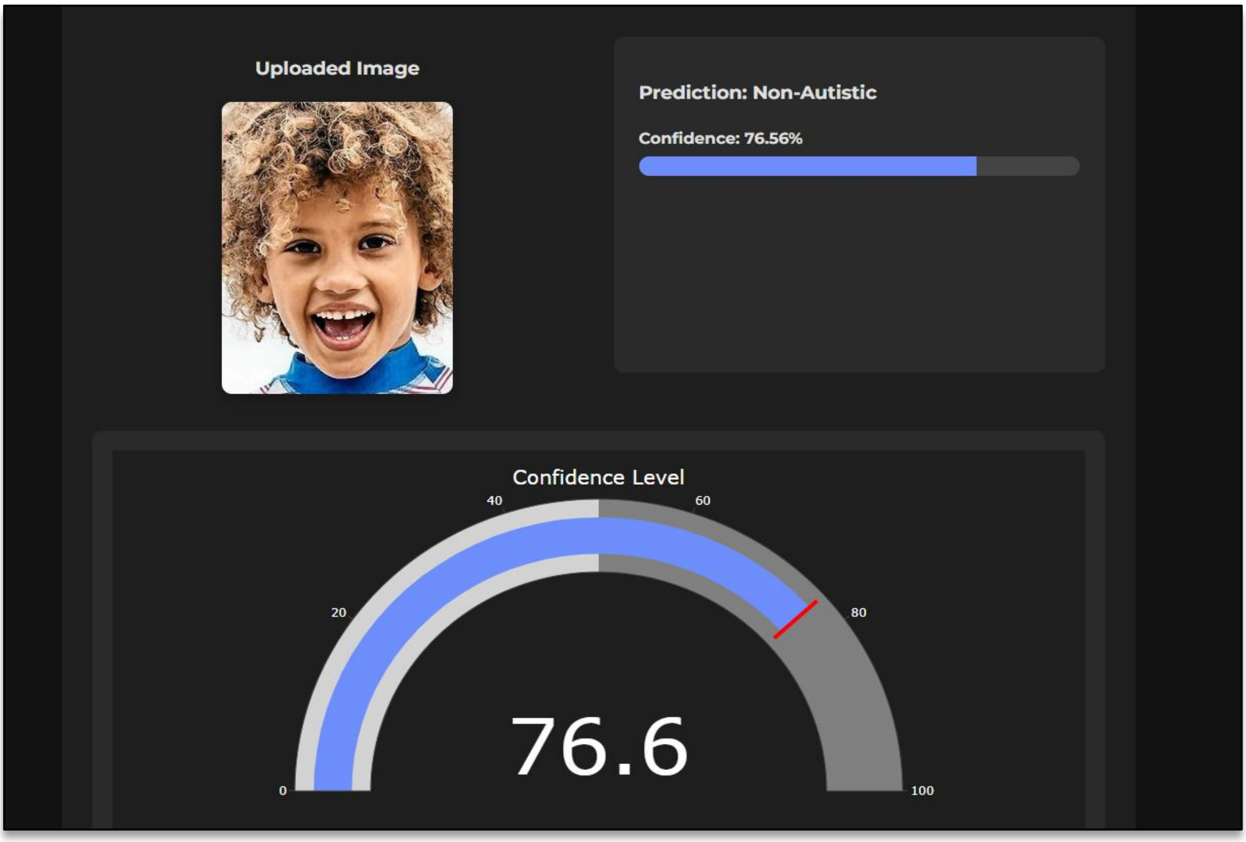

Fig 9: Final Output

VII. CONCLUSION

In conclusion, the proposed system for Autism Spectrum Disorder (ASD) prediction in children using Convolutional Neural Networks (CNNs) demonstrates the potential of deep learning in early and non-invasive diagnosis. By utilizing facial image data and the VGG19 model for feature extraction, the system efficiently classifies images into ASD and non-ASD categories with high accuracy. The integration of preprocessing techniques and model fine-tuning enhances performance and reliability. This approach not only aids in quicker screening but also supports healthcare professionals in early intervention. With further development, such systems can become powerful tools in real-world clinical settings, contributing to better management and understanding of ASD.. The use of image preprocessing, data augmentation, and advanced training strategies such as early stopping and the Adam optimizer contributed to the robustness and accuracy of the model. Furthermore, the deployment of the trained model through a Flask-based web application with MySQL integration demonstrates the feasibility of real-time, accessible ASD screening in clinical or home settings. The proposed system not only accelerates the diagnostic process but also minimizes the burden on healthcare professionals and parents by providing a non-invasive, low-cost solution. While the results are encouraging, future work could focus on increasing dataset size, improving model interpretability, and incorporating multi-modal data (e.g., behavioral or eye-tracking data) to further enhance diagnostic reliability and clinical acceptance.

VIII. FUTURESCOPE

The ASD prediction system holds significant potential for future enhancements and broader applications. Future work can focus on expanding the dataset to include diverse age groups, ethnicities, and image conditions to improve model generalizability. Integration with multimodal data—such as behavioral patterns, speech analysis, or genetic markers—could further increase prediction accuracy.

1. **Real-Time Diagnosis**: Enable real-time analysis and instant feedback for users by optimizing model performance for faster predictions.
2. **Adaptive Learning**: Incorporate continuous learning from user feedback and new data to keep the system up-to-date and improve over time.
3. **Clinical Collaboration**: Partner with healthcare providers to validate the system clinically and support integration into real-world diagnostic workflows.

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4. **Explainable AI**: Enhance transparency and trust by implementing explainable AI techniques to show why the system makes certain predictions.

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