Proceedings of 14th IOE Graduate Conference
Peer Reviewed
Year: 2023 Month: December Volume: 14
ISSN: 2350-8914 (Online), 2350-8906 (Print)

Autism Spectrum Disorder Detection using Facial Landmark Detection and Artificial Neural Network

Sanjaya poudel [a], Saroj Doranga [b], Bidhya Poudel [c], Bibek Chalise [d], Suwan Babu Bastola [e], Hari Prasad Pokhrel [f], Rajeev Nepal [g], Sudip Poudel [h], Pratigya Timsina [i]

[a] *Universal Engineering and Science College, Lalitpur, Nepal*
[b] *Informatics and Intelligent System Engineering, Thapathali Campus, IOE, Tribhuvan University, Nepal*
[c, d] *Paschimanchal Campus, IOE, Tribhuvan University, Nepal*
[e] *Nepal Telecom, Kathmandu*
[f] *Election Commission of Nepal, Kathmandu, Nepal*
[g] *Universal College of Medical Sciences and Teaching Hospital (UCMS-TH), Ranigaon, Bhairahawa, Nepal*
[h] *B.V.Sc and A.H, AFU, Rampur, Chitwan, Nepal*
[i] *Prithvi Narayan Campus, Tribhuvan University, Pokhara, Nepal*
[a] poudelsanjay52@gmail.com, [b] 9846656375saroj@gmail.com, [c] bidhyapoudel436@gmail.com, [d] work.bibekchalise@gmail.com, [e] suwanbastola@gmail.com, [f] hpokhrel24@gmail.com, [g] nepalrajeev11@gmail.com, [h] sudippdl206@gmail.com, [i] pratigyatimsina324@gmail.com

Abstract

Autism Spectrum Disorder (ASD) represents a multifaceted challenge under intensive examination within the realms of child psychology and neurodevelopment. Presently, conventional diagnostic methods heavily lean on subjective expert judgments, incurring both substantial time and financial costs.This study pioneers an innovative approach to ASD classification by synergizing the power of Artificial Neural Networks (ANNs) with facial landmark detection. Our methodology intricately scrutinizes children's facial features, extracting and analyzing facial landmarks from images. This technique capitalizes on the subtleties embedded in these intricate details.Beyond this, the study delves into binary classification, a machine learning task that dichotomizes data into one of two distinct classes or categories. Additionally, Principal Component Analysis (PCA), a dimensionality reduction technique, plays a pivotal role in transforming data into a more compact representation while retaining essential variance, thereby simplifying complex data and facilitating feature selection. Remarkably, our model's performance on a publicly available research dataset is exceptional, boasting an impressive overall accuracy rate of 88.19 percentage. With training and testing losses of 0.311 and 0.4392, respectively, our model maintains an accuracy rate of 80.92percentage. It further excels with a ROC AUC score of 0.889, underscoring its high efficacy. Although we acknowledge the inherent limitations of our strategy, our unwavering commitment to propelling the field of ASD detection is resolute. We are resolutely dedicated to harnessing the full potential of Deep Learning and Artificial Neural Networks, charting a course toward substantial advancements in ASD diagnosis.

Keywords

Artificial Neural Network, Autism Spectrum Disorder, Binary Classification, Facial Landmark Detection, PCA

1. Introduction

1.1 Background

Autism is a neurodevelopmental disorder that conditions social interaction, behavior, and communication. According to a survey, 75% million people have autism spectrum disorder which is around 1% of the entire world. In 100 children, it is estimated to have autism in 1 child as of 2021 [1]. In the United States, every one of 36 children are diagnosed with autism. ASD detection has become a serious issue in developing and underdeveloped countries. Early Diagnostics of ASD become challenging because most of the expression like language, eye movement, and facial expression is difficult to analyze in a 12-18 months period child [2]. Research shows that it is difficult to identify ASD even at the age brackets of 4 years in the different states of the United States [3]. According to WHO, different factors lead to autism problems such as environmental, and genetic [4]. Because of such factors, autism can be classified into different types, each of which may have different treatments and responses [5]. Symptoms of autism can be observed in eye movement and contact, movement of the head towards different signals like sound, social interactions, communication skills, and repetitive behavior [2]. Some research also claims that in children who have autism their social interaction learning progress and IQ level are very poor [6].

An emerging theory holds that ASD children's aberrant behavior may result from early brain adaptation to a challenging environment rather than from persistent neurological dysfunction [3].The early years of a child's life are marked by rapid brain development. As a result, identifying and addressing issues at an early stage can prevent the brain from becoming accustomed to unfavorable conditions and greatly improve the overall outlook. Previous studies have shown that a child's brain flexibility diminishes as they grow older, making it clear that early intervention can substantially boost a child's language and cognitive abilities when behavioral challenges initially surface[7]. With a population of over 7 billion people and the expansion of such problems, innovative caregiving strategies are required. Techniques like question answering with parents and analysis of different videos of children at an early age are used to identify the early symptoms [7]. Different Machine Learning and Artificial Intelligence Techniques are used for the early diagnosis of ASD. Artificial Neural Network for the detection of ASD, which provides 100% accuracy [8], so machine learning and AI algorithms provide more accuracy. Despite this technology screening and monitoring are also used for the diagnosis of ADS, which is quite time-consuming and less accurate [6].

1.2 Facial Landmark Detection

Facial landmark detection is the process of locating and detecting specific points or landmarks on a face, such as the nose, eyes, and chin. The objective is to accurately identify these landmarks from still photos or moving videos of faces in real-time and use them for a variety of tasks, including face recognition, facial expression analysis, and head pose estimation. A facial landmark detector needs to be accurate, efficient, and portable to be useful. Numerous facial recognition algorithms have been developed in the past that can automatically identify key features in images and videos. Facial landmark detection algorithms are specifically crafted to automatically pinpoint these landmarks within facial images or videos. These significant points can be categorized as either interpolated points, which link the prominent points surrounding facial features and the facial outline, or as prominent points that precisely define the specific location of a facial component, such as the corner of the eye[9]. Particularly in computer vision and facial recognition, facial landmarks are particular features or areas on a person's face that act as reference points for various applications. These distinguishing characteristics include the chin, corners of the mouth, nose, and eyes. To recognize faces, track facial emotions, and even calculate variables like gender and age, sophisticated algorithms analyze the spatial correlations between these locations. Security, healthcare, and entertainment all benefit from the use of facial landmark technology, which also has the potential to revolutionize fields like biometrics and augmented reality by making accurate facial tracking and analysis possible for a variety of useful and imaginative uses [8]. Carette et al. (2018)[6], expressed the aid of machine learning techniques and eye-tracking technology, and the authors developed an automatic method for diagnosing autism spectrum disorders. Chang et al. (2017) showed that a straightforward convolutional neural network (CNN) can predict the six degrees of freedom (6DoF) 3D head pose accurately and consistently. [10].

2. Literature Review

Autism Spectrum Disorder (ASD) represents a multifaceted challenge in the realms of child psychology and neurodevelopment.The current diagnostic landscape predominantly relies on expert opinions, a method fraught with subjectivity, time constraints, and financial burdens. Recent years have seen a growing interest in harnessing the power of machine learning for ASD diagnosis. This includes investigations into various data sources, such as neuroimaging and behavioral data, to develop predictive models. Facial features have emerged as potential biomarkers for ASD, with studies suggesting distinct facial characteristics among individuals with ASD. Moreover, the application of Artificial Neural Networks (ANNs) has gained prominence in the healthcare domain, offering the capacity to discern intricate patterns from data. Principal Component Analysis (PCA) further complements this endeavor by efficiently reducing data dimensionality while preserving essential information. Notably, limited research has combined facial analysis with machine learning for ASD diagnosis. Therefore, this study endeavors to bridge this gap by proposing an innovative approach that amalgamates ANNs with facial landmark detection for ASD classification. By doing so, it aims to provide a more objective and efficient diagnostic method, laying the groundwork for advancements in ASD detection.

- Research by [11] concluded the model's effectiveness in understanding individual attention behaviors within the ASD spectrum. The paper suggests that the method is more suitable for capturing unique attention characteristics of each child with ASD rather than generalizing across the spectrum. Future work may involve assessing its applicability to other demographic factors like age and gender and conducting real classroom-based studies for comparative analysis.
- Work done by [12] concluded that they proposed two deep learning techniques for behavior detection, one based on raw video frames and the other on facial features. For predicting Autism Spectrum Disorder (ASD), they explored feature selection, class balancing, and neural network classifiers to connect behavior statistics with ASD diagnosis and future plans involve incorporating time-based analysis for better behavior detection, using audio for vocalization detection, and implementing self-supervised methods to identify objects and adult faces in images to enhance gaze tracking.
- Hornet University's Lab has created a mobile application called "detector" designed to capture a subject's responses to a video presenting resulting scenes. This configuration revealed that individuals diagnosed with Autism Spectrum Disorder (ASD) displayed a decreased inclination to switch their attention and exhibited a general deficit in attention[13]. Although automated tools were utilized to detect head orientation and emotional reactions, their ability to identify behaviors associated with ASD was not explored.
- The clinical implications remain limited, primarily because research in genetics and imaging has shown that Autism Spectrum Disorder (ASD) is not typically attributed to a specific gene or a highly localized brain abnormality [14]. Instead, it is believed to stem from a combination of genetic predispositions and disruptions in early neural pathways that are not yet fully comprehended. Although the idea of continuous traits contributing to ASD is appealing to many scientists, it is crucial to acknowledge that these traits, such as intelligence, language abilities, activity levels, anxiety, motivation, and aggressive behavior, intricately interact with each other. Therefore, simplistic models do not adequately capture the complex nature of development.

Research by [15] concluded from a perspective in the realm of AI and Artificial Neural Networks (ANNs), when addressing the well-being of individuals with Autism Spectrum Disorder (ASD) and their families on a global scale, it's beneficial to shift the focus away from merely filling gaps within current systems. Rather, it could be more effective to prioritize solutions that cater to the specific needs and goals of children and adults with ASD. This involves embracing innovative approaches, including the adaptation of evidence-based interventions to suit low-resource environments and empowering front-line healthcare professionals to implement these solutions.

3. Methodology

3.1 Data Collection

In this innovative project, we employed an unique deep-learning approach to detect Autism in Children. Facial expression and landmarks are captured in order to classify Autism in children. For this project, we used an open-source research standard dataset from Kaggle [16]. The dataset consists of 2936 images of children with classes as autistic and non-autistic. The dataset is perfectly balanced.

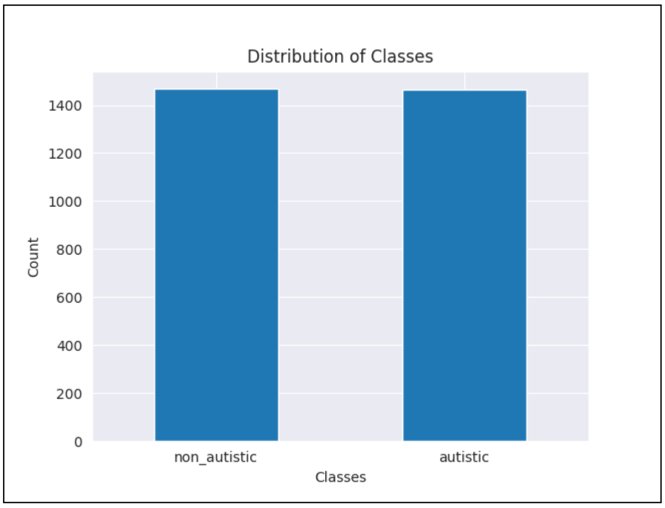

Figure 1: Class Distribution

3.2 Instrumentation

The software and hardware components chosen for this project play pivotal roles in enabling the development and execution of our innovative ASD classification methodology. On the software front, we employ deep learning frameworks such as TensorFlow or PyTorch for implementing and training Artificial Neural Networks (ANNs), while leveraging computer vision libraries like OpenCV or Dlib for accurate facial landmark detection. Essential data processing, analysis, and visualization are facilitated by Python libraries like NumPy, Pandas, and Matplotlib. Additionally, Scikit-learn aids in data preprocessing and evaluation. On the hardware side, we rely on GPU acceleration, typically from NVIDIA GPUs, to expedite the training of complex models, ensuring efficiency even with extensive datasets. Sufficient RAM and storage space are crucial for seamless data handling, and a robust internet connection supports cloud-based resources and dataset acquisition. Together, this software and hardware ecosystem empowers our research to explore new horizons in ASD diagnosis.

3.3 Workflow

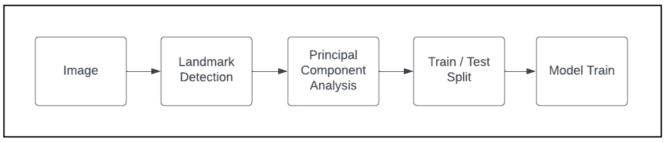

Figure 2: Proposed Workflow

Figure 3: Non-Annotated Image-A

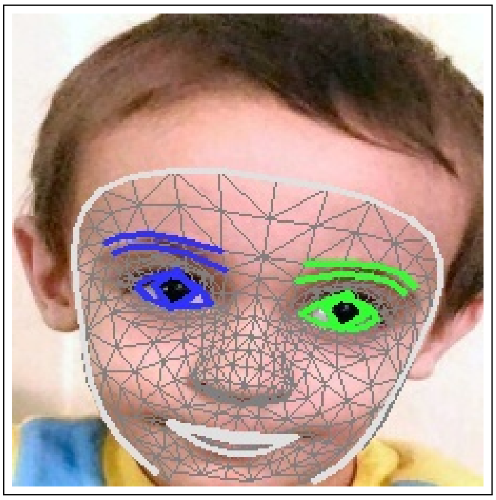

Figure 4: Annotated Image-A

Obtaining a set of images was the first step in gathering data; these images were then processed through a Landmark detector to extract facial landmarks.The system workflow begins with the crucial step of data collection, where a comprehensive dataset of facial images of children, encompassing individuals both diagnosed with Autism Spectrum Disorder (ASD) and those without, is amassed. Once the dataset is established, the next pivotal phase involves the application of facial landmark detection techniques. This process meticulously identifies and extracts essential facial landmarks from the collected images, pinpointing critical facial features such as eyes, nose, and mouth. With these landmarks in hand, the subsequent step revolves around feature extraction, wherein relevant measurements and attributes are derived from the detected facial landmarks. These extracted features could encompass distances between landmarks, angles, or other intricate facial characteristics that hold diagnostic value.

To prepare the data for machine learning, a crucial data preprocessing step follows, which may include data normalization and the division of the dataset into separate training and testing sets. Dimensionality reduction is then introduced using Principal Component Analysis (PCA). PCA plays a pivotal role in simplifying the dataset by reducing its dimensionality while retaining critical variance, thereby enhancing computational efficiency and aiding in feature selection.

Figure 5: Non-Annotated Image-B

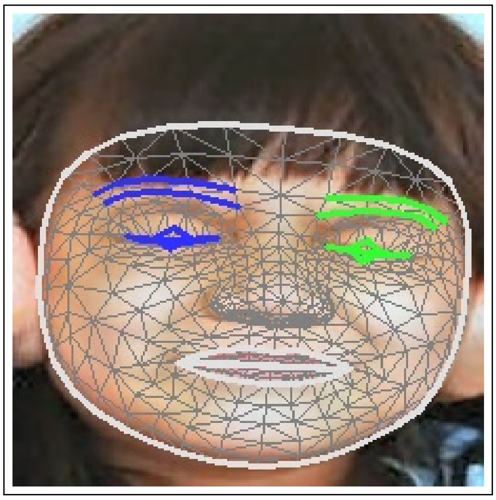

Figure 6: Annotated Image-B

The heart of the system lies in the Artificial Neural Network (ANN), meticulously designed to perform binary classification. The ANN is trained to discern between two distinct categories: individuals with ASD and those without. The model iteratively refines its parameters, optimizing weights and biases to minimize the loss function, during the model training phase. Following the training phase, the model's performance is rigorously evaluated using the testing dataset. Multiple performance metrics, including overall accuracy, loss, and ROC AUC score, are computed to gauge the effectiveness of the model in ASD classification.

In the final stage of the workflow, the project's findings and results are scrutinized and analyzed. The project's success is evident through the achievement of an impressive overall accuracy rate of 88.19 percentage, as well as training and testing losses that underscore the model's efficacy. Furthermore, the ROC AUC score of 0.889 accentuates the model's high performance. While the project acknowledges certain inherent limitations, such as the potential for data bias and the need for further research, the commitment to advancing ASD detection through deep learning and artificial neural networks remains steadfast. This project endeavors to pave the way for substantial advancements in the field of ASD diagnosis, offering a promising avenue for future research and innovation.

Once these landmarks were extracted, they were organized and stored as a dataset. To enhance the dataset's suitability for modeling, a dimensionality reduction technique was applied to reduce the data's dimensionality.

After the dimensionality reduction process, the dataset was partitioned into two subsets: a training set and a test set, with an 80/20 split. The final step involved training an artificial neural network (ANN) on the pre-processed data[17].

3.4 Landmark Detection

In our research, we used the Machine Learning tool named MediaPipe [18] Face Landmarker developed by Google, which enables us to analyze intricate details from facial images and videos.This technology allows us to precisely identify facial landmarks, which are essentially specific coordinate locations in either 2D (with x and y coordinates) or 3D (with x, y, and z coordinates).

Figure 7: Non-Annotated Image-C

These landmarks correspond to key facial features like the corners of the lips and eyes, various points along the eyebrows, the positions of the irises, and even the contours of the face itself. Additionally, it provides intermediate points along the cheeks and forehead. Remarkably, this process extracts 478 times 3 points from the face, yielding a total of 1,434 feature columns. So, our research explores a wide rich dataset of 1,434 features of each image. The Facial Landmarker is a package of model components, including model cards such as the Face Detector [19] , FaceMesh-V2 [20], and Blendshape [21]. Figures which represent the face landmarks detected by the MediaPipe Facial Landmark are represented here.

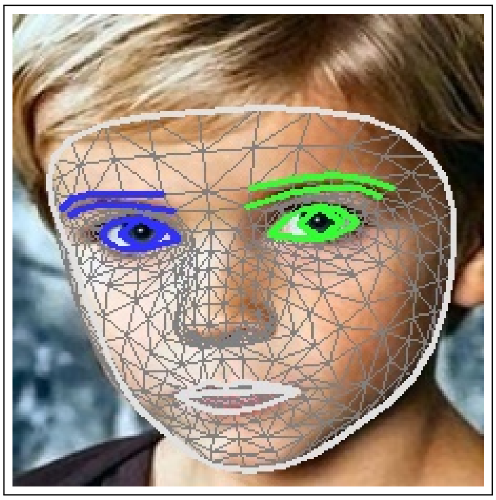

Figure 8: Annotated Image-C

3.5 Dimensionality Reduction

Since the facial landmarks were already correctly scaled, there was no need for additional scaling operations. However, working with a dataset that contains 1434 feature columns can impose a significant computational burden on models. To mitigate this computational load, we introduced Principal Component Analysis (PCA) as a dimensionality reduction technique. This enabled us to reduce the number of features by half, making it more manageable for subsequent modeling and analysis [22].

3.6 Model Architecture

The selected neural network architecture for this project is a Sequential neural network, which is a foundational type of artificial neural network known for its linear stacking of layers. At its core, it encompasses an Input Layer, which serves as the initial point of entry for data into the network. The shape of this layer is determined by the number of features present in the training data, allowing it to seamlessly accommodate varying input data dimensions. Following the Input Layer, the neural network architecture incorporates multiple Hidden Layers, which play a pivotal role in capturing intricate patterns and relationships within the data. The Hidden Layers in this network are densely connected, which implies that every neuron in a layer is linked to each neuron in the preceding and succeeding layers. To introduce non-linearity and empower the network to effectively model complex functions, Rectified Linear Unit (ReLU) activation functions are employed on the output of these Hidden Layers.

To stabilize training and expedite convergence, Batch Normalization layers are added after each dense Hidden Layer, except the Output Layer. These layers normalize activations to have zero mean and unit variance, preventing gradient vanishing issues and expediting training. To combat overfitting, Dropout Layers are strategically positioned, deactivating some neurons during training iterations, promoting robust feature learning.

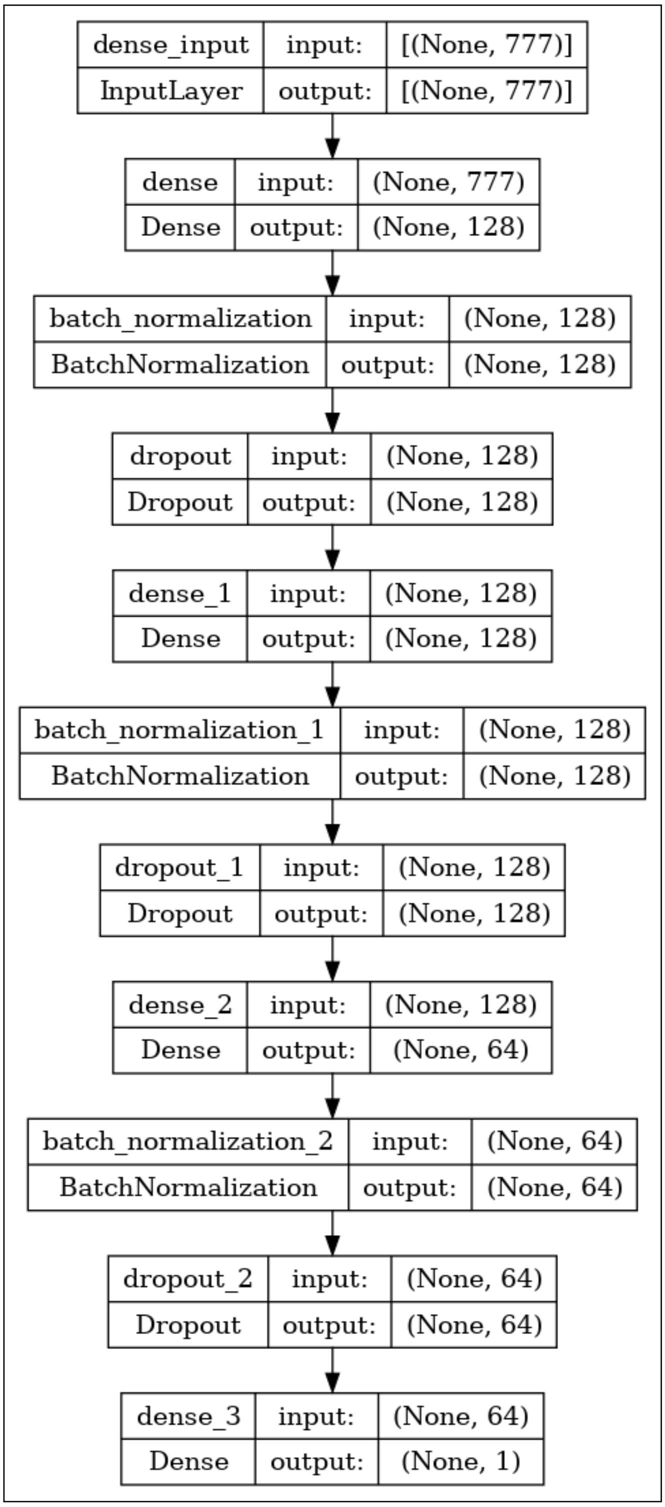

Figure 9: Model Architecture

The Output Layer is designed for binary classification, featuring a single neuron with a sigmoid activation function, producing outputs in [0, 1], indicating the likelihood of input belonging to one of two categories.This neural network model is designed for binary classification tasks, making it versatile for various real-world applications, including image classification and sentiment analysis. To enhance training and optimize performance, it employs a dynamic Learning Rate

Schedule based on the Keras ReduceLROnPlateau callback, which adjusts the learning rate as needed during training. Additionally, it utilizes the efficient Adam optimizer with an initial learning rate of 0.001 and employs binary cross-entropy loss, effectively quantifying dissimilarity between predicted probabilities and actual binary labels to guide parameter adjustments for optimal model convergence.

Lastly, the model is compiled, bringing together all the defined components and configurations. The chosen loss function (binary cross-entropy) and optimizer (Adam) are assigned to the model. Moreover, accuracy is used as the evaluation metric, enabling the ongoing evaluation of the model's capacity to accurately classify data throughout the training process. This comprehensive architecture and configuration provide a robust framework for effectively addressing binary classification challenges, while the dynamic learning rate schedule and advanced optimization techniques contribute to the model's adaptability and convergence efficiency.

We trained the model with batch size of 512 for 200 epochs. For training the model, we used Python programming langugage, OpenCV for image reading, Tensorflow Keras API for model building model architecture. Kaggle Cloud Notebook was used for model training.

3.7 Evaluation Metrics

We used various evaluation metrics to assess the performance of our model. The metrics indicated crucial information regarding the effectiveness of our model.

1. **Receiver Operating Characteristic (ROC) Area Under the Curve (AUC)** Creating a plot of the True Positive Rate (TPR) and False Positive Rate (FPR) at different thresholds leads to the construction of the ROC AUC (Receiver Operating Characteristic Area Under the Curve)[?]. Among all genuine positive cases, the TPR stands for the sensitivity and represents true positive predictions. When referring to all actual negative cases, FPR stands for the percentage of false positive predictions.

$$\text{ROC AUC} = \int_0^1 \text{Sensitivity}\, d(\text{False Positive Rate}) \quad (1)$$

2. **Accuracy** The evaluation metric accuracy generally provides a summary of the model's capability to predict both positive and negative classes. It is calculated by dividing the proportion of correctly predicted instances by the total number of instances in the dataset.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (2)$$

3. **Specificity (True Negative Rate, TNR)** Specificity measures the model's ability to correctly identify non-ASD cases, showing the proportion of true negatives among all actual negatives.

$$\text{Specificity} = \frac{\text{True Negatives}}{(\text{True Negatives} + \text{False Positives})} \quad (3)$$

4. **Loss** When training and optimising models, the loss function is a key component. It is quantified how much of a difference there is between the predicted values and the actual target values. For our binary classification task, we used binary cross-entropy loss (BCE-Loss), which evaluates the disparity between true labels and predicted probabilities.

$$\text{BCE Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log(p_i) + (1-y_i)\log(1-p_i)\right) \quad (4)$$

5. **Recall (Sensitivity, True Positive Rate, TPR)** Recall quantifies the model's ability to correctly identify all actual ASD cases, indicating the proportion of true positives among all actual positives.

$$\text{Recall} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Negatives})} \quad (5)$$

4. Results and Discussion

In the comprehensive evaluation of our model's performance throughout the project, we encountered notable successes that underscore its efficacy. Notably, during the training phase, our model achieved an outstanding maximum accuracy score of 88.19%, showcasing its adeptness at learning patterns from the training dataset. This success provides a robust foundation for its learning capabilities. Furthermore, when applied to the test dataset, our model demonstrated commendable performance with an accuracy rate of 80.92%. This result is indicative of the model's ability to generalize its acquired knowledge from the training data to make precise predictions on novel instances.

In addition to accuracy, we diligently monitored the loss metric, a pivotal indicator of how effectively our model approximates the underlying data distribution. The meticulous training efforts resulted in minimized loss values of 0.311 for the training dataset and 0.4392 for the test dataset. These reduced loss values signify the model's proficiency in minimizing errors during the learning process, ultimately enhancing its overall performance. This thorough analysis and the positive outcomes observed underscore the robustness and effectiveness of our model in the context of Autism Spectrum Disorder detection using Facial Landmark Detection and Artificial Neural Networks.

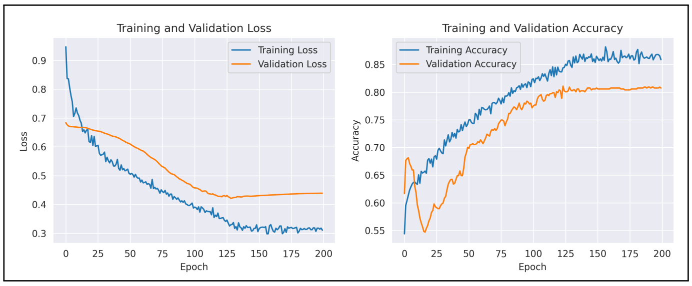

Figure 10: Accuracy and Loss plot (Train V/S Test dataset)

In our evaluation of the model's ability to differentiate between classes, the Receiver Operating Characteristic Area Under the Curve (ROC AUC) Score emerged as a crucial metric, exhibiting an impressive value of 0.889. This notable ROC AUC score signifies the model's exceptional capability to make informed and precise predictions, further emphasizing its robustness in handling intricate data. The high ROC AUC score adds an additional layer of confidence to the overall performance assessment, highlighting the model's efficacy in discriminating between different classes relevant to Autism Spectrum Disorder detection using Facial Landmark Detection and Artificial Neural Networks.

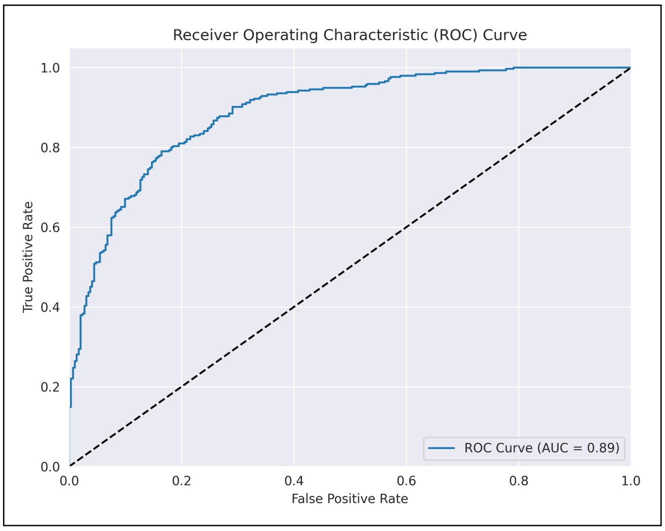

Figure 11: The ROC AUC Curve

By delving into the Confusion Matrix, we gained valuable insights into both the strengths and weaknesses of our model. This analysis allowed us to identify specific areas where the model demonstrated exceptional accuracy and pinpoint those instances where improvements were needed. Examining various categories within the Confusion Matrix provided a nuanced understanding of the model's performance, enabling us to fine-tune and enhance its capabilities. This meticulous evaluation has been instrumental in refining our approach to Autism Spectrum Disorder detection, guiding us towards continuous improvement and a more nuanced comprehension of the model's behavior across diverse scenarios.

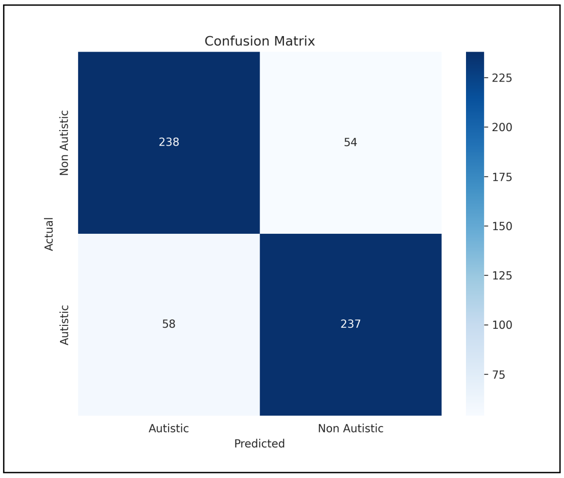

Figure 12: Confusion Matrix Plot

5. Limitations and Future Works

5.1 Limitations

In our study, we developed a cutting-edge method for locating facial landmarks in children with Autism Spectrum Disorder (ASD). Through the use of an Artificial Neural Network (ANN), we processed these facial landmarks after first identifying them. The results obtained using this approach showed promise, indicating the possibility of its usefulness as an important tool in the classification of ASDs. However, it is essential to acknowledge certain limitations of our project such as our project solely relies on facial expression, but ASD is influenced by other things such as behavioral and physical traits, and reactions to verbal or textual stimuli. Also, Individuals exhibit a wide range of facial expressions. So, classification just based on facial cues could result in misunderstanding.

5.2 Future Works

Several directions for future research and development should be investigated in order to improve the efficacy and practicality of our strategy: We have highlighted a few future works for this project as listed below:

1. **Use of functional magnetic resonance imaging (fMRI) data and electroencephalography (EEG) signal**:

   In our upcoming research, we plan to incorporate functional magnetic resonance imaging (fMRI) data and electroencephalography (EEG) signals. An effective approach for autism detection involves the integration of fMRI (functional magnetic resonance imaging) data and EEG (electroencephalogram) signals. EEG records electrical activity while fMRI reveals patterns of brain activation. Combining these techniques improves our comprehension of the neurological markers of autism, which could help with earlier and more precise diagnosis and individualized treatment, and further our understanding of the disorder as a whole.

2. **Moving to a Video-Based Detection Method:**

   Our project can capture dynamic behavioral cues if it switches from image-based detection to video-based detection. We can follow children's physical behaviors and movements using video analysis, which gives us a richer source of data for diagnosing ASD.

6. Conclusion

In a nutshell, our study is a significant step towards using facial landmark detection to identify children with ASD. Despite the positive nature of our findings, we acknowledge that diagnosing ASD is a complex process that calls for a multidisciplinary strategy. The following are the main points to be undertaken from this research project.

1. **Facial Landmark Identification** The core of our approach is the accurate recognition of facial landmarks in people with ASD. These landmarks act as important visual cues that might help with the diagnosis of ASD.

2. **Processing with Artificial Neural Networks** After identifying facial landmarks, we used Artificial Neural Networks (ANNs) to further process the data. In their capacity to identify patterns and relationships in large, complex datasets, ANNs have demonstrated promise.

3. **Positive Results** The results produced by our method were positive and encouraging. They emphasized the method's potential as a useful tool in the arsenal for classifying ASDs.

Future works will be focused on improving our methodology, diversifying datasets, and fusing complementary approaches. Additionally, functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) signals can be employed for the early diagnosis of Autism Spectrum Disorder (ASD), allowing for the assessment of spontaneous brain activity associated with ASD. We hope to contribute to the creation of more thorough and accurate ASD diagnostic tools with practical applications by addressing these issues.

References

[1] DSMTF American Psychiatric Association, American Psychiatric Association, et al. *Diagnostic and statistical manual of mental disorders: DSM-5*, volume 5. American psychiatric association Washington, DC, 2013.

[2] Yvette Hus and Osnat Segal. Challenges surrounding the diagnosis of autism in children. *Neuropsychiatric disease and treatment*, pages 3509–3529, 2021.

[3] Kelly A Shaw, Matthew J Maenner, Jon Baio, Anita Washington, Deborah L Christensen, Lisa D Wiggins, Sydney Pettygrove, Jennifer G Andrews, Tiffany White, Cordelia Robinson Rosenberg, et al. Early identification of autism spectrum disorder among children aged 4 years—early autism and developmental disabilities monitoring network, six sites, united states, 2016. *MMWR Surveillance Summaries*, 69(3):1, 2020.

[4] Holly Hodges, Casey Fealko, and Neelkamal Soares. Autism spectrum disorder: definition, epidemiology, causes, and clinical evaluation. *Translational pediatrics*, 9(Suppl 1):S55, 2020.

[5] Maryellen Brunson McClain, Amber M Hasty Mills, and Laura E Murphy. Inattention and hyperactivity/impulsivity among children with attention-deficit/hyperactivity-disorder, autism spectrum disorder, and intellectual disability. *Research in developmental disabilities*, 70:175–184, 2017.

[6] Gillian Baird, Tony Charman, Antony Cox, Simon Baron-Cohen, John Swettenham, Sally Wheelwright, and Auriol Drew. Screening and surveillance for autism and pervasive developmental disorders. *Archives of disease in childhood*, 84(6):468–475, 2001.

[7] Halim Abbas, Ford Garberson, Eric Glover, and Dennis P Wall. Machine learning approach for early detection of autism by combining questionnaire and home video screening. *Journal of the American Medical Informatics Association*, 25(8):1000–1007, 2018.

[8] Ibrahim M Nasser, Mohammed Al-Shawwa, and Samy S Abu-Naser. Artificial neural network for diagnose autism spectrum disorder. *International Journal of Academic Information Systems Research (IJAISR)*, 3(2), 2019.

[9] Rajeev Nepal, Saroj Doranga, and Pratigya Timsina. Knowledge and attitude on mental disorder among adults in putalibazar municipality of syangja district of nepal. *Progress in Health Sciences*, 11:23–30, 2021.

[10] Feng-Ju Chang, Anh Tuan Tran, Tal Hassner, Iacopo Masi, Ram Nevatia, and Gerard Medioni. Faceposenet: Making a case for landmark-free face alignment. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 1599–1608, 2017.

[11] Bilikis Banire, Dena Al Thani, Marwa Qaraqe, and Bilal Mansoor. Face-based attention recognition model for children with autism spectrum disorder. *Journal of Healthcare Informatics Research*, 5:420–445, 2021.

[12] Chongruo Wu, Sidrah Liaqat, Halil Helvaci, Sen-ching Samson Chcung, Chen-Nee Chuah, Sally Ozonoff, and Gregory Young. Machine learning based autism spectrum disorder detection from videos. In *2020 IEEE International Conference on E-health Networking, Application & Services (HEALTHCOM)*, pages 1–6. IEEE, 2021.

[13] Saroj Doranga, Rajeev Nepal, and Pratigya Timsina. Stock market prediction using machine learning. *Multi-Disciplinary Explorations: The Kasthamandap College Journal*, 1(1):98–114, Oct. 2023.

[14] Catherine Lord, Mayada Elsabbagh, Gillian Baird, and Jeremy Veenstra-Vanderweele. Autism spectrum disorder. *The lancet*, 392(10146):508–520, 2018.

[15] Rajeev Nepal, Jyoti Priyanka, Pradip Chhetri, Suruchi Godar, Pratigya Timsina, and Saroj Doranga. Factors associated with problematic alcohol consumption among adults in putalibazar municipality of syangja district, nepal. *Advances in Public Health*, 2022:1–7, 2022.

[16] Tania Akter, Mohammad Hanif Ali, Md Imran Khan, Md Shahriare Satu, Md Jamal Uddin, Salem A Alyami, Sarwar Ali, AKM Azad, and Mohammad Ali Moni. Improved transfer-learning-based facial recognition framework to detect autistic children at an early stage. *Brain Sciences*, 11(6):734, 2021.

[17] Warren S McCulloch and Walter Pitts. A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, 5:115–133, 1943.

[18] Abien Fred Agarap. Deep learning using rectified linear units (relu). *arXiv preprint arXiv:1803.08375*, 2018.

[19] Camillo Lugaresi, Jiuqiang Tang, Hadon Nash, Chris McClanahan, Esha Uboweja, Michael Hays, Fan Zhang, Chuo-Ling Chang, Ming Yong, Juhyun Lee, et al. Mediapipe: A framework for perceiving and processing reality. In *Third workshop on computer vision for AR/VR at IEEE computer vision and pattern recognition (CVPR)*, volume 2019, 2019.

[20] Valentin Bazarevsky, Yury Kartynnik, Andrey Vakunov, Karthik Raveendran, and Matthias Grundmann. Blazeface: Sub-millisecond neural face detection on mobile gpus. *arXiv preprint arXiv:1907.05047*, 2019.

[21] Viv Bewick, Liz Cheek, and Jonathan Ball. Statistics review 13: receiver operating characteristic curves. *Critical care*, 8(6):1–5, 2004.

[22] Karl Pearson. Liii. on lines and planes of closest fit to systems of points in space. *The London, Edinburgh, and Dublin philosophical magazine and journal of science*, 2(11):559–572, 1901.