Eye Tracking Scanpaths for Classification of Autism Spectrum Disorder: Leveraging LSTM-Based Models

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Eye Tracking Scanpaths for Classification of Autism Spectrum Disorder: Leveraging LSTM-Based Models

Major Project - II

Submitted in partial fulfillment of the requirements

for the degree of

Master of Technology in Computer Science and Engineering (Data Science)

Submitted By

Jainish Patel

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Guided By

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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Certificate

This is to certify that the major project entitled **"Eye Tracking Scanpaths for Classification of Autism Spectrum Disorder: Leveraging LSTM-Based Models"** submitted by **Jainish Patel (Roll No: 21MCED07)**, towards the partial fulfillment of the requirements for the award of degree of Master of Technology in Computer Science and Engineering (Data Science) of Nirma University, Ahmedabad, is the record of work carried out by him under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination. The results embodied in this major project part-II, to the best of my knowledge, haven't been submitted to any other university or institution for award of any degree or diploma.

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Statement of Originality

I, **Jainish Patel**, Roll. No. **21MCED07**, give undertaking that the Major Project entitled "**Eye Tracking Scanpaths for Classification of Autism Spectrum Disorder: Leveraging LSTM-Based Models**" submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in **Computer Science & Engineering (Data Science)** of Institute of Technology, Nirma University, Ahmedabad, contains no material that has been awarded for any degree or diploma in any university or school in any territory to the best of my knowledge. It is the original work carried out by me and I give assurance that no attempt of plagiarism has been made.It contains no material that is previously published or written, except where reference has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

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Guide Name

(Signature of Guide)

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Abstract

The neuro-developmental condition known as autism spectrum disorder (ASD) is characterised by difficulties in social interaction and communication as well as the prevalence of restricted and repetitive behaviours. Early ASD diagnosis is essential for successful intervention and better results. Eye tracking technology has been a useful technique for investigating social cognition and identifying possible ASD signs in recent years. This study uses eye tracking scan pathways captured during a computer-based task to examine the classification of children with ASD and children who are Typically Developed (TD). We suggest using a Long Short-Term Memory (LSTM) model as the core of our classification strategy. With 99.0% accuracy on the training data and 97.4% accuracy on the validation data, the model performs quite well. While participants complete a task requiring social cueing and gaze cueing on a computer screen, eye tracking data is being gathered. The inclusion of social cueing tasks enables us to evaluate the participants' social cognitive skills, which are known to be impaired in people with ASD. We seek to uncover distinctive patterns and features within the eye tracking scan paths that distinguish ASD and TD participants by utilising the temporal dynamics collected by LSTM models. The results of this study add to the expanding body of work on using machine learning and eye tracking approaches for diagnosing and evaluating ASD. A non-invasive and objective method for early identification of ASD is provided by the potential for reliably differentiating TD children from children with ASD based on eye tracking scan trajectories, allowing for prompt intervention and support. Furthering our understanding of the underlying mechanisms underlying this complex condition, our findings further offer light on the function of social cognition and gaze cueing in ASD.

Abbreviations

TD	Typically Developed
ASD	Autism Specturm Disorder
DL	Deep Learning
LSTM	Long Short-Term Memory
CSV	Comma Separated Values

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Chapter 1

Introduction

Autism spectrum disorders (ASD) are a broad category of abnormalities. Individuals struggle with interpersonal engagement and conversation to a certain extent. Unconventional behaviors of behaviors and responses, like difficulty transitioning through one task to the next, a concentration on minutiae, and unexpected response to stimuli, are also features[1]. Autistic people's capabilities and requirements fluctuate and might change through the period. Although few persons having autism may be able to function individually, others experience great difficulty that necessitate ongoing attention and supervision. Autism frequently affects educational and economic prospects[2].

Furthermore, the obligations placed on households offering help and treatment might be substantial. The standard of living of individuals having autism is influenced by society's views and the quantity of help offered by public entities.The term "autism spectrum disorder" (ASD) refers to a group of disorders that include issues with conversational contact, challenges with mutual interpersonal connections, and atypical repetitions of repeated behaviors or hobbies[3]. Establishing and keeping visual connection while casual engagement isn't necessarily simple or effortless for those with ASD diagnoses. However, these worrying inadequacies may put a lot of stress on people's life and those of their family. Nonetheless, cognitive impairment or general growth retardation do not provide a more compelling explanation for these abnormalities[4].

The growing prevalence of smartphones, along with improvements in AI technology, particularly computer vision, are making medical technologies more accessible to previously disadvantaged communities. Despite the fact that autism affects one out of every kid, approximately 80% of areas in the United States need exposure to autism diagnosis[5]. As a consequence, people in remote locations and poorer socioeconomic neighborhoods will frequently have to spend about a year with an autism assessment. This protracted and unreasonable latency is especially troublesome in cases of pediatric cognitive impairments such as autism, when faster detection and behavioral therapies lead to better treatment results[3].

Early detection can result from initial assessment, that really is typically advantageous for both the parents as well as the individual. Typically, a determination is made through a series of procedures which can take hours of professional assessments or depending on a conversation with the guardians. The classification of ASD has been also confounded by the wide range of characteristics related to social interaction and communications difficulties, as well as social communications problems and constrained, repeating ways of behaving. Computer aided technology has been adopted in this regard to offer beneficial direction during the duration of testing and evaluation. Good examples are electroencephalogram (EEG), magnetic resonance imaging (MRI), and eye movements, which will all be taken into consideration in this research[6].

Because anomalies of eye movements have continuously been identified also as distinguishing features of autism in broad, eye-tracking technologies have drawn special interest in the domain of ASD. Several different eye tracking psychiatric research have focused on the unique characteristics of visual attention in reaction to either sensory or verbal stimuli as indications of ASD[7]. Particularly whenever facial cues are utilized (as in a face-to-butterfly categorized visual exploration exercise and inappropriate retrieval of visual data via eye fixations for sentiment classification), such research have shown progressive issues in individuals with Autism.

Fixation, saccade, and blinking are the three primary types of gaze that eye monitors are designed to record[8]. A fixation is the relatively long period of time when the sight is stopped on an object to allow the brain to carry out the sensory activity. The usual fixation time spans between 150 and 300 milliseconds. Furthermore, the situation affects how long the fixation lasts. While reading on print (230 ms), viewing content on a display (553 ms), or viewing a realistic scenario on a computer, human fixations last for different amounts of time (330) ms)[9]. Furthermore, proper judgment necessitates frequent item tracking and quick visual acuity known as saccades. Saccades involve brief, rapid leaps that last between 30 and 120 milliseconds (ms). Alternatively, a blink frequently indicates that the mechanism has misplaced control of the eye focus. For a feasible way to represent gaze behavior visually, sight scan paths have been widely employed[10]. A scan path can intersect with its own and reflects a series of subsequent fixations and saccades as a trail through time and space.

Eye traceability involves recording, following, and analyzing visual stimuli or even the actual position of gaze (POG), that designates the location of the eye's focus within a video sequence[11]. As anomalies of gazing have continuously been identified as the distinguishing feature of autism in particular, the eye-tracking technique attracted special focus in the area of Autism. Numerous research in the psychiatric field have examined eye patterns in reaction to auditory or nonverbal stimuli as indicators of Autism.

With the help of this research, eye movements and deep learning can be used to assist in the assessment of ASD. In recent years, there has been growing interest in leveraging advanced machine learning techniques for autism classification. Specifically, the utilization of Long Short-Term Memory (LSTM) models has emerged as a promising approach to distinguish between individuals with Autism Spectrum Disorder (ASD) and typically developing (TD) children. One particularly intriguing avenue of investigation involves the analysis of eye tracking scan paths, with fixation, saccade, and blink patterns serving as crucial parameters. By employing LSTM models to capture and analyze these intricate ocular behaviors, researchers aim to develop accurate and reliable classification systems that can effectively discern ASD individuals from their TD counterparts. This innovative methodology holds great potential for enhancing early diagnosis and intervention strategies, ultimately promoting improved outcomes for individuals on the autism spectrum.

Chapter 2

Literature Survey

There is mounting proof that the use of ML can have a significant influence on the results of autism. This article tries to discuss some of the most current developments in model designs and statistical modeling. Autism Spectrum Disorder can be detected at an early age of 18 months or in some cases even before that age if the child shows such signs in terms of behavior and communication. Many research studies have tried to develop effective methods based on machine learning algorithms to find such patterns through various methods and tried to reach a classification conclusion using collected various types of data and analyzing them with their developed models[9].

The process of diagnosing autism has long been recognized as a challenging, subjective, and costly procedure, heavily reliant on behavioral assessments, historical information, and parental reports. In an effort to enhance existing diagnostic methods, previous research has proposed the use of machine learning classifiers as potential screening tools or complementary approaches. One such classifier focused on analyzing eye movements of individuals while navigating web pages, although it only considered non-sequential data. By combining data from multiple web pages, this classifier achieved optimal accuracy, albeit with varying levels of success on different pages. In this present study, the authors aimed to investigate the feasibility of detecting autism based on eye movement sequences, while striving for consistent accuracy across diverse web pages to avoid dependence on specific contexts.

To achieve this, they employed Scanpath Trend Analysis (STA), a technique designed to identify trending paths of user gaze on web pages. Initially, trending paths were identified for both individuals with autism and neurotypical individuals. Subsequently, the authors determined a person's likelihood of having autism by calculating the similarity between their gaze path and the trending paths of both groups. If the path resembled the trending path of neurotypical individuals more closely, the person was classified as neurotypical; otherwise, they were classified as having autism. The proposed approach was thoroughly evaluated using an eye-tracking dataset consisting of 15 verbally proficient and highly independent individuals with autism, as well as 15 neurotypical individuals, across six different web pages. Results demonstrated that the STA approach exhibited superior performance on individual web pages and provided more consistent accuracy across different pages, offering a promising avenue for autism detection and diagnosis[7].

The early detection of autism spectrum disorder (ASD) has improved significantly due to increased screening efforts and general awareness. However, there remains a dearth of knowledge regarding the long-term prognosis for children who are identified at a young age. It is widely understood that the developing brain is influenced by experience-dependent mechanisms, with visual attention playing a crucial role in shaping brain development[7]. As a result, eye tracking technology has emerged as a promising tool for identifying prognostic markers in children with ASD. This study focused on 49 children between the ages of 1 and 3 years who were diagnosed with ASD. They participated in an eye-tracking test called the GeoPref Test, which aimed to assess their preference for social versus nonsocial images.

Subsequently, the children underwent a comprehensive test battery when they reached school age, approximately 5 to 9 years after the initial GeoPref Test. Statistical analyses were conducted to determine whether eye-tracking measurements during early childhood could predict later outcomes in symptom severity, social functioning, adaptive behavior, joint attention, and IQ. The findings revealed that toddlers who exhibited a stronger preference for geometric images during the GeoPref Test displayed higher levels of symptom severity and fewer gaze shifts during school-age assessments. However, no significant associations were observed with IQ or adaptive behavior. These results suggest that the GeoPref Test holds promise as a prognostic tool for predicting symptom severity in individuals with ASD. Furthermore, the development of additional eye-tracking paradigms may enhance the predictive power of such assessments and prove valuable in validating the effectiveness of treatment interventions. Further research in this area is warranted to expand our understanding of the prognostic potential of eye tracking in ASD and its implications for personalized interventions[12].

Numerous researchers attempted to use eye tracking for the investigation and evaluation of ASD. For example, Vabalas and Freeth (2016) used eye tracking studies to illustrate fascinating neurobiological concepts. Eye patterns during face-to-face conversations varied across people who were located at distinct points on the autism spectrum. Particularly, quicker and fewer saccades were noted in people with higher levels of autistic characteristics. Another work employed eye-tracking to determine kids with ASD using the length of fixings & the frequency of saccades (Pierce et al., 2011). Their findings demonstrated that relative to similar classes, persons with ASD invested noticeably longer duration trying to focus on dynamic geometrical patterns[13].

One of the initial researchers to examine visual stimuli in kids and teenagers with ASD was Rosehall, Johansson, and Christopher. They noticed strange microsaccades motion and mentioned having trouble keeping their eyes on a shifting subject. However, it wasn't until Van der Geest started using accurate eye monitoring gadgets to objectively compare the visual stimuli of ASD kids and their Intelligence quotient typical classmates. Since then, there have been additional studies looking into unique gaze behavior in ASD. Researchers utilized stationary cues in the manner of illustrations visuals in their research and discovered that the both parties' fixation tendencies were comparable.

They created the groundwork for conducting gaze monitoring work in pediatric and teenage neuropsychology and drew many comparable experiments as an outcome of their work, particularly in order to precisely grasp visual stimuli and sensory processing in Autism. As a response, numerous unusual ocular focuses linked to Autism have been discovered. It has been demonstrated that a child's identification of Autism and an infant's prolonged disconnecting interest from a previously observed region are related[14]. In addition, gaze-tracking experiments have revealed other deficits such the failure to distribute cognitive capacity across the area of vision and the tendency to focus on fewer culturally relevant items[15].

Chapter 3

Proposed Research Work

3.1 Participants for the Dataset

N = 100 adolescents between the ages of 10 and 13 were included in the research. They were divided into two categories: normally developing (TD) individuals and Autism Spectrum Disorder (ASD) individuals[16]. Of these, four individuals had poor data level (e.g., inaccurate oculomotor details due to poor measurement, inability to properly calibrate, various answers on more than fifty percent of tests, pressing buttons prior to and at the beginning of pursuit providing precise division not possible, etc.), three of them had insufficient evaluation discussions, 3 had an IQ below 70, 2 had an identification of an assessment disorder, 3 had an undisputed detection.

These individuals were added according to prior results of Wechsler Intelligence Scale for Children IQ testing and after checking with the doctors in impose, however they were omitted from IQ associations and ANCOVAs with IQ as a covariate. In all, N = 77 participants' information has been incorporated in the study[17]. The Department of Child and Adolescent Psychiatry, University Medical Centre Freiburg, evaluated and selected all experimental group members. All evaluations were established using the ICD-10 Standards by trained doctors[14]. The Autistic Prognosis Observation Checklist and the Autism Diagnostic Interview-Revised, the gold standards for Autism Diagnosis, were used to make the final determination[13].

The TD members were selected via the division's database, which included data from participation in neighbourhood educational institutions and athletic teams keen on joining the research, as well as marketing via University Hospital Freiburg personnel. A phone call with the guardians was utilised to check that the TD group participants had no known mental or neurological background. Seven participants had Enuresis, six had Adjustment Disorder, one had Social Phobia, one had Specific Phobias, one had Childhood Emotional Disorder, one had Depressive Episodes, one had Dyscalculia, one had Specific Spelling Disorder, one had Developmental Dyspraxia, four had Expressive Language Disorder, two had Tic Disorder, one had Somnambulism, and one had Obsessive-Compulsive Disorder.

The Child Behaviour Checklist (CBCL) and Social Responsiveness Scale (SRS) were completed by the guardians of every subject as a baseline assessment for general psychological asymptomatology and autism symptoms, accordingly. Subjects were asked not to take any stimulant medicine on the morning of the exam. The two subgroups were age-matched, and barely any between-group variations in IQ (as measured by the Culture Fair Intelligence Test 20 (CFT 20-R)) or gender were detected. Scientists gathered surveys as supplemental tools for enhancing collective assessment. Furthermore, these were employed in isolated circumstances where doctors could offer information about a participant's involvement in the group[18].

3.2 Equipment Used

Stimuli had a 1920 x 1080 pixel resolution, were generated in black, and were displayed on a white context. The objects were shown using Presentation® software (Version 17.2). SensoMotoric Devices GmbH's RED250 eye monitor was used to capture the gaze at a sampling rate of 120 Hz. Five members of the clinical groups and four members of the control teams had their gaze recorded at a frequency of 60 Hz due to a specific malfunction. Both regardless of these subjects, statistical evaluation revealed that the important values were constant. Fixation was determined to be occurrences with a minimum time span of 60 ms and a maximum spread of 2° using BeGaze 3.7 (SensoMotoric Instruments GmbH), which was also utilised to save event information, create scan paths, and do exploratory analysis[17].

3.3 Procedure

Gazes were collected as subjects sat roughly 70 cm in front of the monitor in a sound-proof booth. The entire experiment lasted 60–90 minutes and included a set of five challenges that were distributed to each member of every group in an offset sequence. The visual hunt task is the main topic of this article. Prior to gathering oculomotor information for the current task, 5-point standardisation and 4-point confirmation steps were properly carried out. The activity began with the experimenter giving subjects organised, step-by-step guidance before they completed two informal trials next to him or her and a ten-trial practise block with frequent input to ensure comprehension. The job's primary phase came after the practise phase[17].

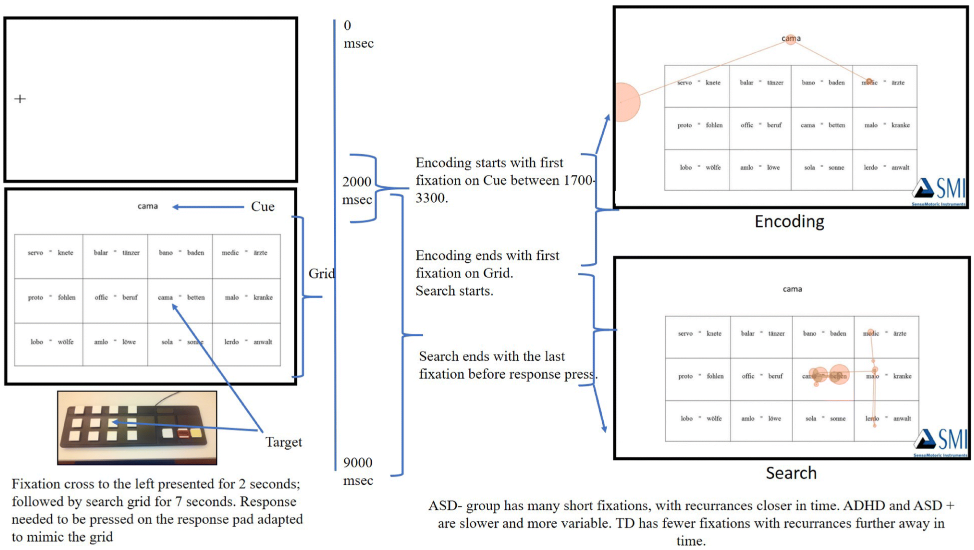

Figure 3.1: Example of a Trial

3.4 Dataset Description

The Eye Tracking data set includes gaze information that was gathered during a trial activity using an eye tracking equipment. The data set attempts to record participants' fixation, saccade, and blinking eye movements while they observe various stimuli. The dataset is intended for classification tasks that separate people with autism spectrum disorder (ASD) from people who are normally developing (TD).

Data Format: The dataset is offered in the commonly used tabular data format CSV

(Comma-Separated Values). As an example, each row in the CSV file represents a single sample of data and includes the following columns.:

- ParticipantID: Unique identifier for each participant in the study.
- TrialNumber: The trial number corresponding to the sequence of stimuli presented during the activity.
- StimulusType: Indicates the type of stimulus presented, which can be a visual image, video, or text.
- FixationDuration: The duration of the fixation in milliseconds (ms), representing the time the eye remained focused on a specific point.
- FixationX: The x-coordinate of the fixation point on the screen.
- FixationY: The y-coordinate of the fixation point on the screen.
- SaccadeDuration: The duration of the saccade in ms, representing the time taken for the eye to move between fixations.
- SaccadeStartX: The x-coordinate of the starting point of the saccade.
- SaccadeStartY: The y-coordinate of the starting point of the saccade.
- SaccadeEndX: The x-coordinate of the ending point of the saccade.
- SaccadeEndY: The y-coordinate of the ending point of the saccade.
- BlinkDuration: The duration of the blink in ms, indicating the time the eye remained closed.

3.5 Explotary Data Analysis

An important stage in comprehending and analysing a dataset is exploratory data analysis (EDA). EDA in the context of the Eye Tracking dataset is looking at the different features and their distributions, spotting trends, and acquiring knowledge to inform more analysis. Following are some procedures for carrying out EDA on the dataset:

- Data Loading: Load the CSV dataset into a suitable data analysis environment or programming language, such as Python.

- Dataset Overview: Start by examining the overall structure and characteristics of the dataset. Check the number of rows and columns, variable names, data types, and any missing values.

- Summary Statistics: Calculate descriptive statistics for numerical variables like FixationDuration, SaccadeDuration, BlinkDuration, etc. This includes measures such as mean, median, standard deviation, minimum, maximum, and quartiles. Summarizing the statistics can help identify any potential outliers or unusual values.

- Class Distribution: Explore the distribution of the Diagnosis variable, which represents the target variable. Determine the balance between ASD and TD samples in the dataset. Visualize the distribution using bar plots or pie charts to understand the class representation.

- Visualization of Eye Movement Parameters: Create visualizations to gain insights into eye movement parameters such as fixation duration, saccade duration, and blink duration. Plot histograms, box plots, or violin plots to observe the distribution and identify any differences between the ASD and TD groups.

- Correlation Analysis: Examine the correlations between different eye movement parameters and the target variable (Diagnosis). Calculate the correlation coefficients (e.g., Pearson's correlation) and visualize them using correlation matrices or heatmaps. This analysis helps identify which eye movement parameters may be more informative for classification.

- Feature Relationships: Explore potential relationships or patterns between different eye movement parameters. Create scatter plots, line plots, or bar plots to visualize the relationships between variables. For example, plot FixationX against FixationY to examine eye movement patterns across the screen.

- Feature Comparison: Compare the distributions of eye movement parameters between the ASD and TD groups. Create side-by-side box plots or violin plots to visualize the differences. Perform statistical tests (e.g., t-tests or Mann-Whitney U tests) to determine the statistical significance of these differences.

- Data Preprocessing: Identify and handle any missing values, outliers, or data quality issues as appropriate. Consider normalization or scaling techniques if necessary.

- Additional Analyses: Depending on the research objectives and specific questions, you can perform additional analyses such as time series analysis of eye movement patterns or feature engineering to extract new meaningful features.

Gaining a thorough understanding of the dataset is the aim of EDA, along with identifying data quality problems and possible links or patterns that may help with future modelling or classification tasks.

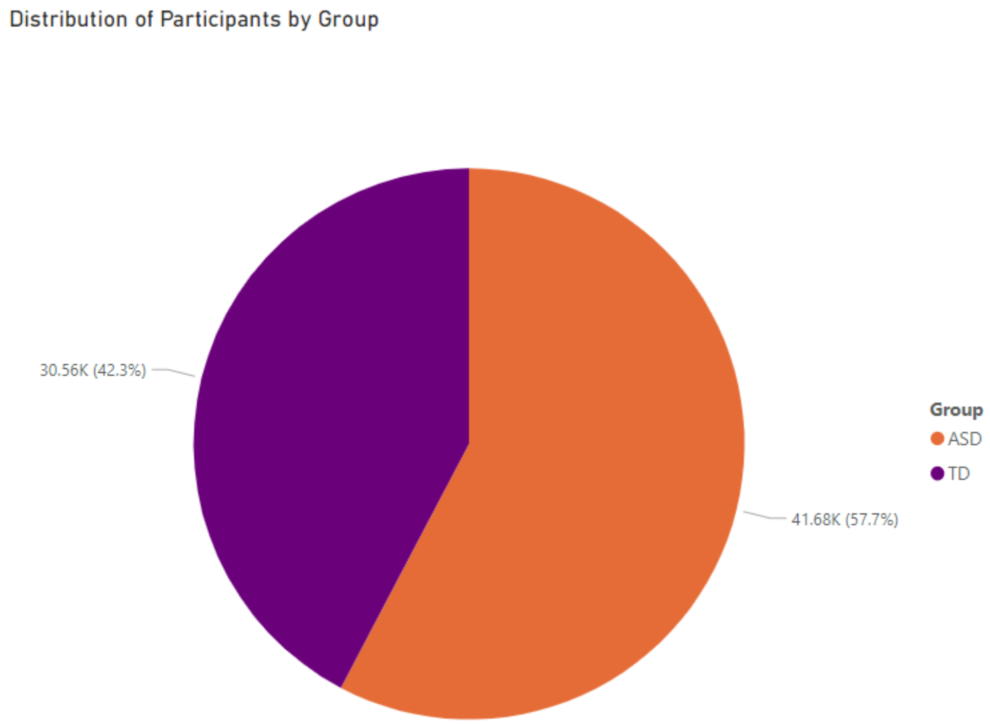

Figure 3.2: Distribution of Participants by Class

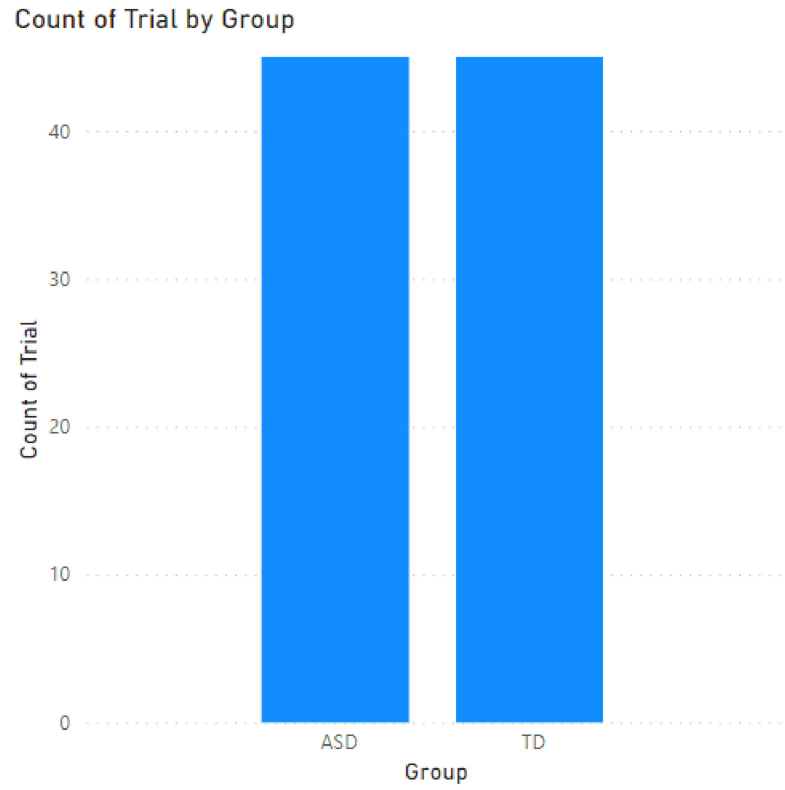

Figure 3.3: Count of Trial by Group

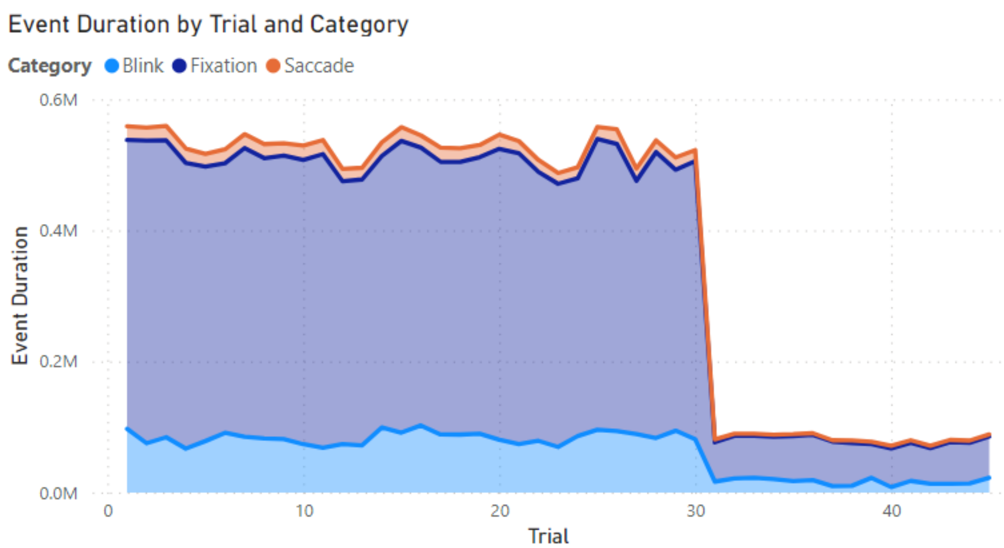

Figure 3.4: Event Duration by Trial and Category

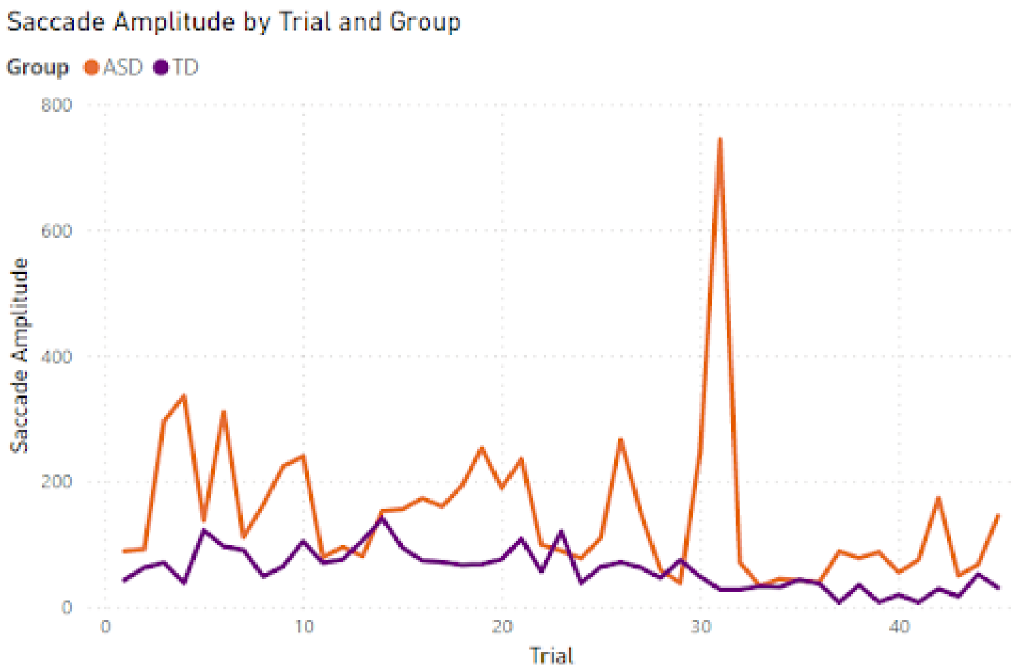

Figure 3.5: Saccade Amplitude by Trial and Group

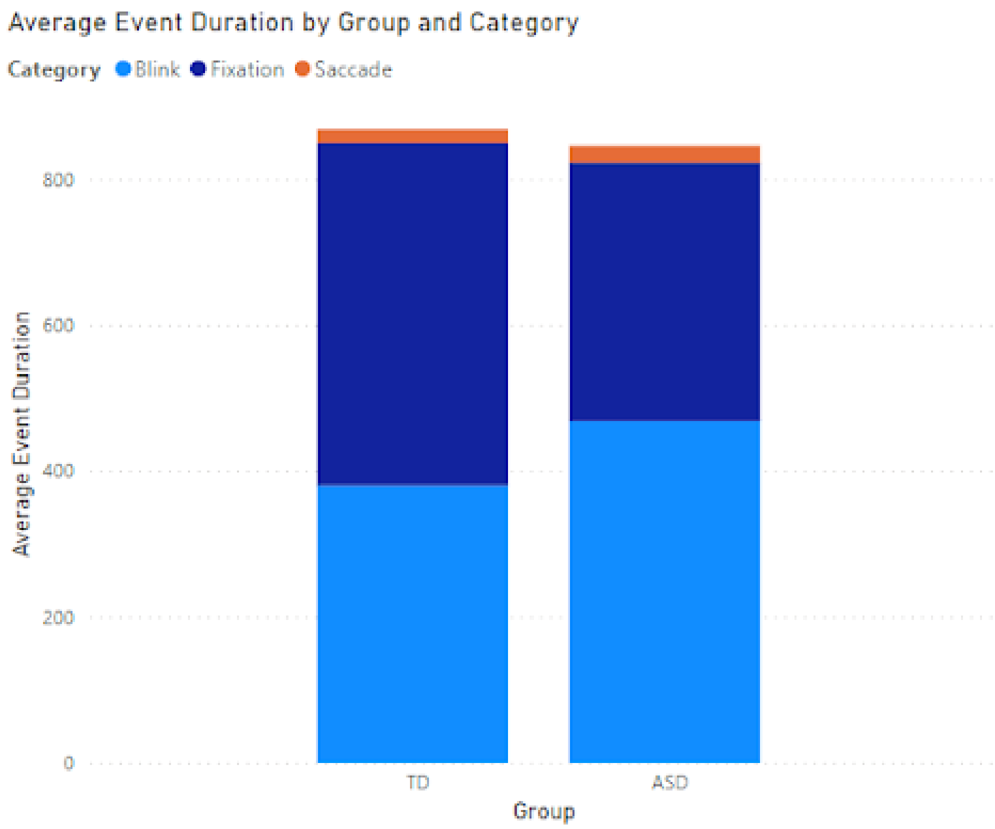

Figure 3.6: Average Event Duration

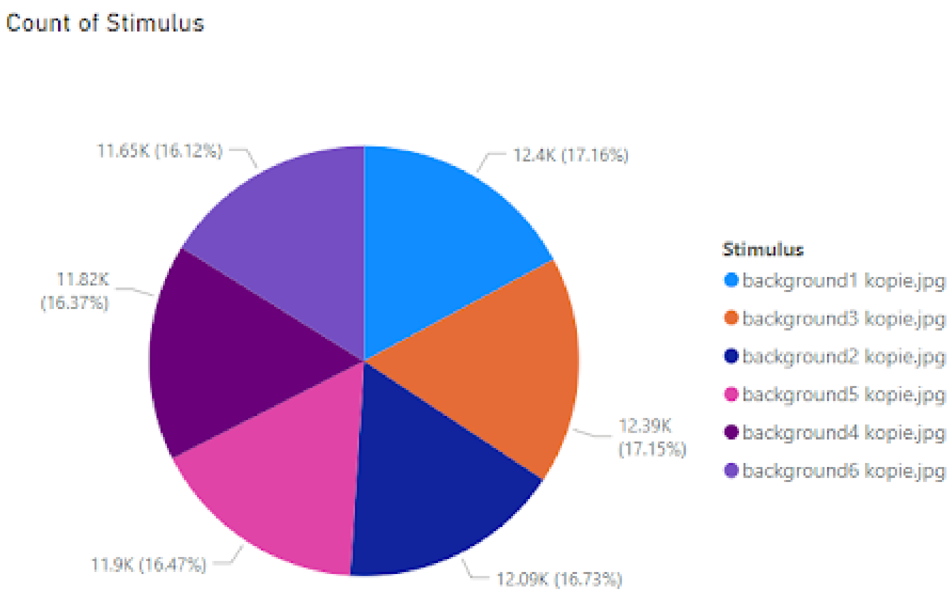

Figure 3.7: Count of Stimulus

Figure 3.8: Fixation Points by Group

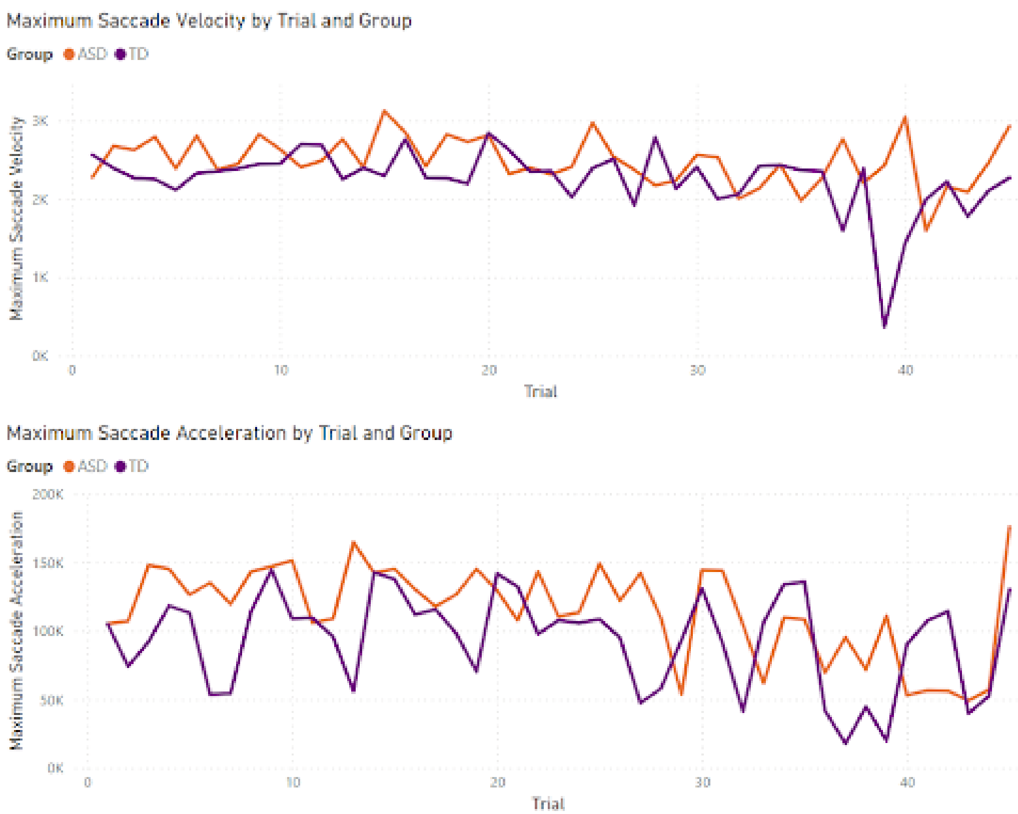

Figure 3.9: Saccade Velocity and Acceleration by Group

Chapter 4

Experiment & Results

4.1 Learning Algorithm

The current study describes an investigation into the use of the Long Short-Term Memory (LSTM) algorithm for categorising people with Autism Spectrum Disorder (ASD) and people who are normally developing (TD) using an EyeTracking dataset. The experiment used the TensorFlow library to create a sequential model with two LSTM units as the input and an output dense layer. L1 and L2 regularisation, as well as dropout regularisation, were introduced into the model architecture to prevent overfitting. The model's performance was enhanced using the Adam optimizer.

The main goal of the experiment was to assess how well the LSTM-based classifier could identify between people with ASD and people with TD based on the eye movement patterns that were recorded by the eye-tracking device. A major emphasis was placed on the model's capacity to generalise and make precise assumptions about unknown data.

Early stopping was used during the training phase to guarantee the model's peak performance and avoid overfitting. This method tracked the validation loss and stopped training after a predetermined number of epochs if no progress was seen. Early halting was used in the experiment to achieve a compromise between properly training the model and preventing unneeded overfitting.

The binary classification task of differentiating between people with ASD and TD was

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 70, 50)            15400

 lstm_3 (LSTM)               (None, 50)                20200

 dropout_2 (Dropout)         (None, 50)                0

 dense_2 (Dense)             (None, 32)                1632

 dropout_3 (Dropout)         (None, 32)                0

 dense_3 (Dense)             (None, 1)                 33

=================================================================
Total params: 37,265
Trainable params: 37,265
Non-trainable params: 0
_________________________________________________________________
None
```

Figure 4.1: LSTM Architecture

chosen as the experiment's loss function, and binary cross-entropy was chosen since it was appropriate. It was possible for the model to identify underlying patterns and generate precise classifications thanks to the loss function, which offered a measure of dissimilarity between the predicted and real labels.

The effectiveness of the model was evaluated thoroughly throughout the experiment. The capacity of the classifier to correctly categorise people with ASD and TD was evaluated using metrics like accuracy, precision, recall, and F1 score. To give a thorough grasp of the model's prediction skills and discriminative strength, visualisations such confusion matrices and ROC curves were also created.

The experimental outcomes and conclusions from this study's research will add to the body of information on how to classify autism using eye-tracking data and LSTM algorithms. The findings from this study could have a big impact on early detection and intervention efforts, which would benefit people with autism spectrum disorders.

4.2 Results

The experimental study's findings show how well the LSTM-based classifier performs when used with the EyeTracking dataset to discriminate correctly between people with Autism Spectrum Disorder (ASD) and people who are normally developing (TD). With training accuracy of 99% and validation accuracy of 97.4%, the model performed admirably.

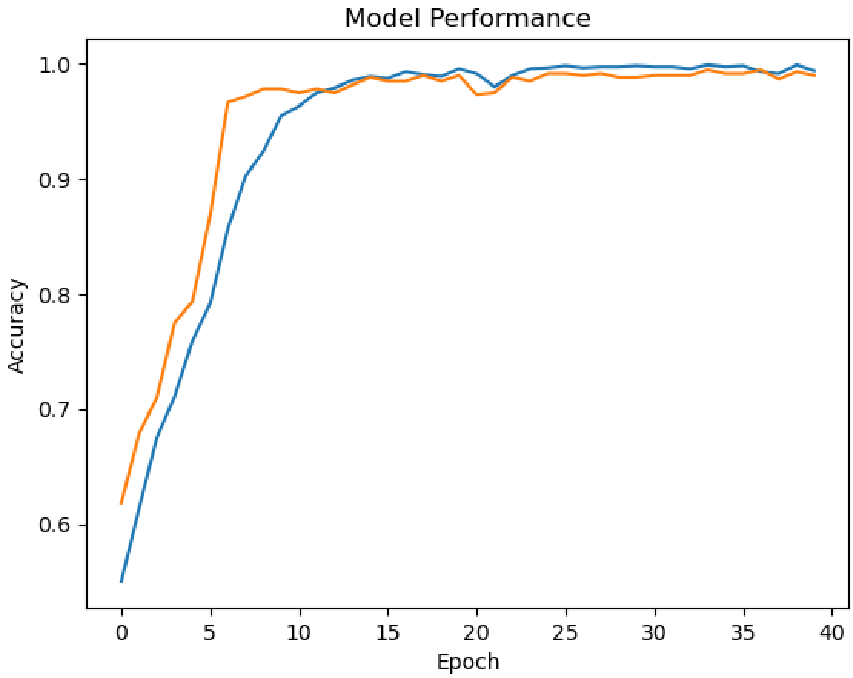

Figure 4.2: Accuracy

The model was able to successfully learn the underlying patterns found in the training data, as evidenced by the high training accuracy, which allowed it to generate precise predictions. The model's capacity to generalise effectively and produce precise classifications on unobserved data is demonstrated by the validation accuracy, which remained continuously high.

To provide a more thorough assessment of the classifier's performance, precision, recall, and F1 score were also computed. The precision metric gauges the model's accuracy in identifying people with ASD by counting the percentage of true positive predictions among all positive predictions. The recall measure, also known as sensitivity, shows how

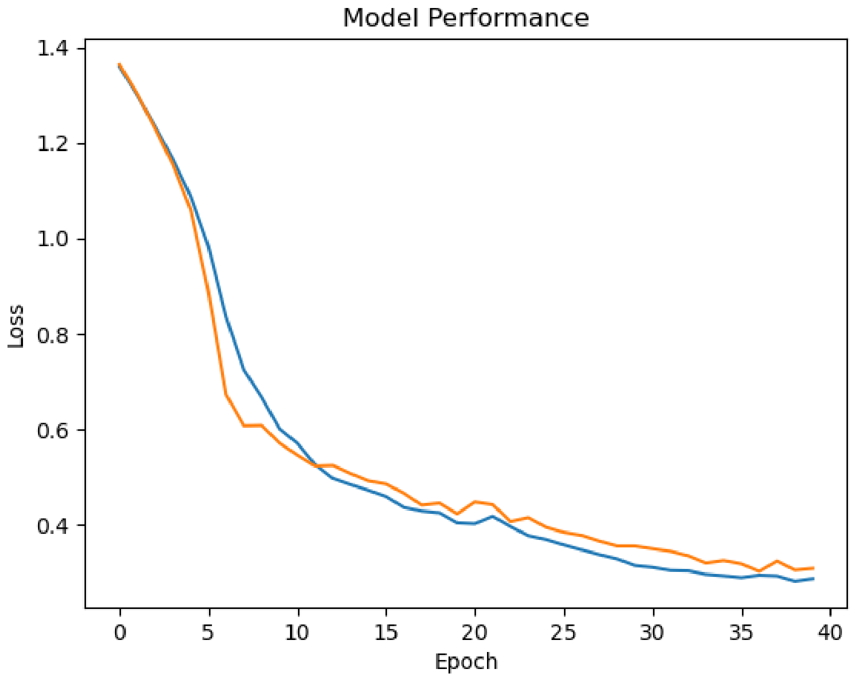

Figure 4.3: Loss

well the classifier can identify people with ASD by showing how many true positive predictions are made out of all real positive cases. The F1 score, which combines precision and recall, provides an overall measure of the model's accuracy.

Further insights into the classifier's predicting skills were gained by creating visualisations like confusion matrices and ROC curves. The confusion matrix provided a thorough insight of the classifier's performance for both ASD and TD classifications by illustrating the distribution of true positive, true negative, false positive, and false negative predictions.

The LSTM-based classifier's outstanding accuracy highlights its potential as a useful tool for correctly classifying people with ASD based on eye movement patterns recorded by the eye-tracking device. The findings of this study have significant ramifications for early identification and intervention techniques in addition to adding to the expanding body of knowledge in the field of classification of autism.

While the achieved accuracy is outstanding, it is vital to keep in mind that additional testing and validation using different datasets are required to determine the suggested

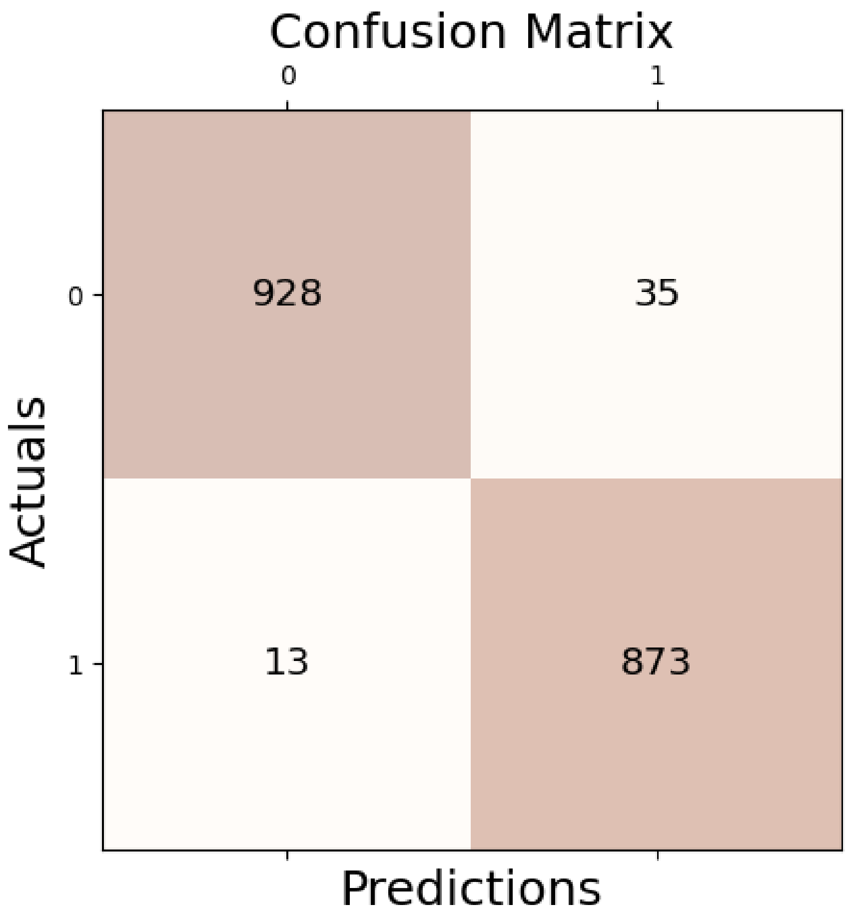

Figure 4.4: Confusion Matrix

classifier's generalizability and dependability. Further study is necessary to investigate these issues, as well as the possibility that the model's performance varies between populations or age groups.

Overall, the findings of this work show the potential of LSTM-based classification models for accurately differentiating between people with ASD and people with TD using eye-tracking data. This study advances our understanding of the subject and establishes the groundwork for future studies aimed at enhancing early identification and intervention methods for people with autism spectrum disorders.

Chapter 5

Conclusion

Using eye movement patterns recorded by an eye-tracking device, this research successfully applies the Long Short-Term Memory (LSTM) algorithm to the classification of people with Autism Spectrum Disorder (ASD) and people who are normally developing (TD). The experimental study's findings show how accurately the LSTM-based classifier performs, with training accuracy of 99 percent and validation accuracy of 97.4 percent.

The results of this study have important ramifications for the early diagnosis and classification of autism. The classifier's excellent accuracy demonstrates its potential as a useful tool for correctly classifying people with ASD based on their eye movement patterns. The suggested classifier is a significant contribution to the field because early detection of ASD is essential for prompt therapies and better results.

Comprehensive evaluations, such as precision, recall, F1 score calculations, and visualisations like confusion matrices and ROC curves, were used to gauge the classifier's robustness and generalizability. These assessments gave the classifier's performance more support and shed light on its forecasting abilities.

While the findings of this study are encouraging, it is vital to recognise that additional research is required to confirm the classifier's effectiveness across a range of demographics and age groups. Additionally, to guarantee the classifier's dependability in real-world circumstances, the generalizability of the classifier should be evaluated using independent datasets.

The LSTM-based classifier's effective implementation demonstrates the promise of machine learning methods to facilitate ASD diagnosis. Early intervention techniques and individualised treatment modalities can be made possible by being able to accurately differentiate between people with ASD and people with TD based on eye-tracking data.

In summary, this research study adds to the body of knowledge regarding the classification of autism and emphasises the significance of utilising cutting-edge machine learning methods for better ASD detection. The results could have a favourable effect on people who are on the autistic spectrum because early detection and intervention can result in improved outcomes and a higher quality of life. Future studies should concentrate on improving the classifier further, assessing its performance in practical situations, and investigating more features or data sources to increase its accuracy and applicability.

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