Analysis and Visualization of Eye movements in Patients with Glaucoma

Sandhiya B.[1], Amudha. J [2], and Sajitha Krishnan [3],
[1] 2 3 Dept. of Computer Science and Engineering, Amrita School of Computing, Bengaluru, Amrita Vishwa Vidyapeetham, India
[1] BL.EN.P2DSC21025@bl.students.amrita.edu
[2] j_amudha@blr.amrita.edu
[3] k_sajitha@blr.amrita.edu

Glaucoma is one of the foremost causes that result in irreversible blindness. World Health Organisation (WHO) has estimated that around 4.5 million people are blind due to glaucoma. This vast number is because more than 90% of glaucoma cases are undiagnosed. Early-stage glaucoma detection system helps to identify the disease and prevent it from further blindness. The proposed system analyzed and visualized the eye movement patterns of glaucoma-affected participants using machine learning algorithms. The model collected eye-gaze patterns using an eye-tracking sensor and visualized them based on different eye gaze features. The model classified glaucoma and normal based on eye gaze data. The proposed model has incorporated different visualization techniques to understand how eye gaze patterns of normal and glaucoma differ while performing screen-based tasks such as Free-Viewing Task and Image Searching Task. The proposed system has also incorporated an interactive dashboard using Microsoft PowerBI Software.

***Index Terms*—Glaucoma, Eye Tracking Sensor, Eye Gaze Patterns, Classification, Power BI Dashboard.**

I. Introduction

Glaucoma is the second cause of irreversible blindness. Structural and functional treatment has to be undergone by the patients for the detection and diagnosis of glaucoma. Numerous works are based on glaucoma detection using retinal fundus images, but few methods exist to understand the gaze patterns of patients with glaucoma. It is well-known that a person affected with glaucoma tends to have restricted eye movements in every day activities such as reading, driving etc. These differing gaze patterns were used to classify a normal and glaucoma-affected person.

Different research articles focused on automated system for glaucoma detection [12], [13], [14], [15], [16]. Various deep learning transfer models employed for detecting glaucoma based on has been reported [1]. Scan path Modelling And Classification with Hidden Markov Model(SMAC with HMM) – a MATLAB toolbox was used for gaze modeling and classification. The model captured gaze behavior's dynamic and individualistic components [2].

The features from the retinal fundus images are automatically extracted using the convolutional neural network instead of using handcrafted features. The extracted features were given to a Support Vector Machine to classify normal and glaucoma [3]. Deep feature extraction using ConvNet (seven different Convnets) was applied on ROI (Region Of Interest) in the retinal fundus image dataset. The feature extracted by these seven nets is then concatenated into a single vector, and finally, SVM was applied for classification [4].

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Machine Learning technique called Support Vector Machine for glaucoma classification. The input of the model was an image dataset, where in the initial stages, the preprocessing required for the image, such as image resizing and filtering, are done and a decomposition technique known as 2D-VMD (2-Dimensional Variational Mode Decomposition) is used. The features are extracted, and the SVM algorithm is applied to selected features. They classify glaucoma into three classes Normal, Early Glaucoma, and Advanced Glaucoma [5].

Different research articles investigated scan path patterns to understand participants' performance in different tasks. String-edit method was applied for analyzing the scan path data [6]. Different cost functions such as City block distance and the Euclidean distance have been experimented with. Multimatch-gaze is a python-based toolkit that helps in comparing the scan path measure [7].

A new tool called ScanGraph has been developed to compare scan paths using the visualization of graph cliques. The scan path comparison is made using the string edit distance. The application is more suitable if the purpose is to find the difference in the gaze movements of a different group of participants [8].

A new algorithm that extracts sequence-sensitive features is used for classification. The sequence-sensitive features are nothing but the scan path feature obtained from the eye movements. Performance analysis of this system with the existing system is also discussed [9]. The automated detection system for glaucoma also incorporated different visualization maps to classify between glaucoma and normal

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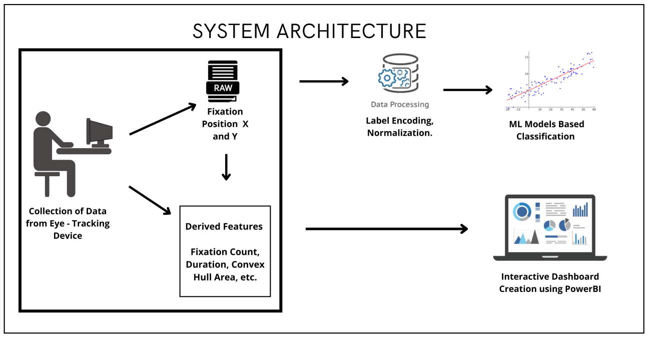

Fig. 1: Proposed System Architecture

while performing different day-to-day tasks [18].

The proposed method analyzed eye gaze data from the Eye Tracker Sensor and visualized it using different charts. Moreover, visualization tools such as Microsoft PowerBI Software were used to get valuable insights into classifying glaucoma and normal.

The next sections of the paper are organized as follows. Section II describes in detail the proposed methodology and various techniques used in it. Section III describes the results observed from the Machine Learning Model and discussion about the insights obtained from various visualization charts. Section IV shows the conclusion of the paper.

II. METHODOLOGY

In the proposed method, the raw data obtained from the eye tracking sensor and the derived data from the raw eye gaze are utilized for analysis and visualize the eye gaze movements of different participants [17]. The proposed methodology aims to analyze and visualize eye gaze data of glaucoma participants. The methodology included a machine learning classifier that classifies glaucoma and normal. The interactive dashboard visualizes the eye gaze parameters of glaucoma and normal to analyze the gaze path of different participants. The proposed system architecture is shown in Fig. 1.

A. Apparatus

A screen-based eye tracker, Eye Tribe 60 Hz is connected to the display screen where computer-based tasks are displayed. The eye tracker directed infrared light towards the centre of the eye. The participant sat at a distance of 60 cm from the monitor. Before the experiment, participants Pupil-Corneal Reflex (PCR) was measured at nine different calibration points, and if necessary, re-calibration is done to ensure that the pupil position of the participants is accurate. After the successful calibration, stimuli were displayed on the screen for the participants.

B. Stimuli

Instructions for various screen-based tasks such as free viewing task and image-searching task were explained to the participants in either English or their native tongue. The eye-tracking data were collected from the participants using an eye-tracking sensor. In the Free-Viewing task, the participants viewed 20 images and were asked to explore the image given a particular time constraint. Stimuli with natural scenes and social scenes were included in the task. [17].

Fig. 2: Stimuli Used for Image Searching Task

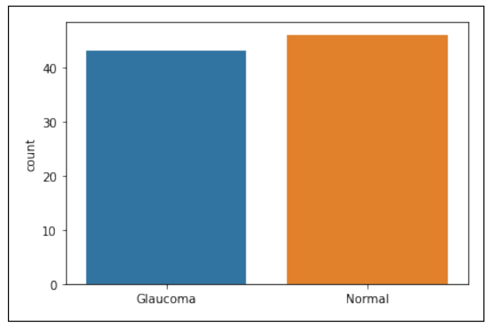

Fig. 3: Count of observations in Actual Class

In the Image Searching Task, a ”Star” was hidden at different positions in 20 different images. The participants were asked to find the hidden star within a stipulated time. Fig. 2 shows a sample of stimulus which was used in the Image Searching Task. The hidden star is marked with a red circle for reference.

When the participants performed those tasks, the raw eye gaze patterns or gaze samples were observed using the eye tracking sensor. The gaze samples are classified into fixations and saccades using event detection algorithm [20]. Fixation is the accumulation of gaze positions on a particular region for a given time. Saccade is the movement of the eye from one fixation to another fixation.

C. Dataset Description

The features in the dataset are briefly explained in Table I. The dataset used for classification is balanced Fig. 3. The inference about how different age group is related to the Class Glaucoma and Class Normal can be obtained from Fig. 4

TABLE I: Description of Features in the Dataset

Sub_Id	Unique identification number given to each participant
Trial_Id	Unique number associated with the stimulus used for different task
Start Time	Time at which a particular participant has started the gaze movement for a particular task
Fixation Length	Total fixation length
posX	Horizontal Gaze position of a participant
posY	Vertical Gaze position of a participant
Age	Age of the participant
Sex	Gender of the participant
Fixation duration	Total duration taken for a fixation
Convex Hull Area	Area that contains collection of fixation points
Actual Class	Class of the participant. Normal or Glaucoma

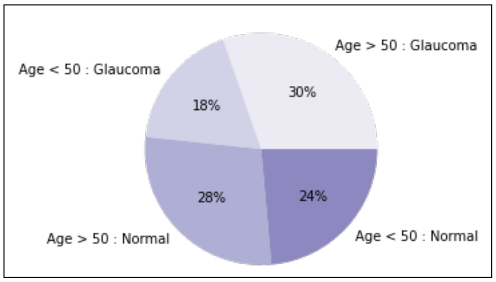

Fig. 4: Relation between Age and Actual Class

Derived attributes based on fixation events such as Fixation Length, Fixation Duration, Convex Hull Area, and Horizontal Vertical ratio (HV ratio) were estimated, which is given as an input for the Machine Learning Model for classification. The dataset used in the proposed methodology comprises these derived eye gaze attributes of Image Searching Task and Free-Viewing Task [17]. The reason behind using the derived attributes for classification was that the derived attributes tend to have more information and dependencies than the raw features. More details about the derived attributes i.e Extracted Features can be inferred from [20].

D. Machine Learning Classifiers

Machine Learning Models help to create an automated system for glaucoma classification. Machine Learning model is applied to different derived attributes for classification of participants into glaucoma and normal. Various classification algorithms such as K-Nearest Neighbor, Support Vector Machine, Na¨ıve Bayes, Logistic Regression, and Decision Tree were implemented and their performance metrics were observed.

KNN algorithm works well for a small dataset. This study also employed a smaller dataset. Logistic Regression is used to assess the relationship between a dependent variable and one or more independent variables, when the dependent variable is binary. In this paper, we are attempting to assess the link between the participants' binary class (dependent variable) and the other independent variables. SVM is a popular classifica tion and regression algorithm that performs well with both linear and non-linear data. Since the work proposed here is for classification, SVM is experimented with. Other classifiers are tested to see how the classifier performs.

E. Visualization

The raw data and derived attributes were used for the purpose of visualization of the gaze pattern of participants for different tasks. The gaze path was plotted with respect to time series to understand fixations while viewing different tasks on the screen. The trace path depicted spatial allocation of eye gaze on the screen. To perform visualization python libraries such as Seaborn and Matplotlib were used. The analysis was made based on the What - Why - How Framework in visualization [19]. The what part of the framework deals with What kind of dataset is being used and various components of the dataset and attributes.

The what part talks about the type of data, dataset, dataset availability, attribute type, and ordering direction. In terms of the proposed methodology, the type of data used will fall into the category of Attributes and Items. Attributes are some specific properties that can be measured, observed, or logged. Here we are measuring various eye gaze features. So, we can tell those features as attributes. An item is an individual entity, such as a row in a simple table. The dataset used for the proposed methodology is in table form. Each row can be considered an item. The dataset type is a table. The Dataset Availability is Static, as the given data is offline and it doesn't change over time.

The Why part of the framework deals with Why the analysis is done. The Why part can be categorized into two components. The first component is Action and the second component is Target. In terms of the proposed methodology, in the Action component, already existing data is consumed to discover new, previously unknown insights. In the Target component, the trend of the eye gaze patterns of participants for various tasks is found.

The How part of the framework deals with How the visualization can be constructed using the set of design choices. The How part consists of different components such as Encode, Facet, Manipulate, and Reduce. In terms of the proposed methodology, the color from Encode and Filter from Reduce are widely used.

III. RESULTS AND DISCUSSION

Our proposed methodology classified the normal and glaucoma participants using eye gaze features. The outcome of the classifier was represented based on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Since the proposed methodology aims to detect glaucoma, minimizing false negatives is more important. Accuracy and Recall were used as the performance metrics.

Accuracy is the correctly predicted observations from the overall observations, which is given in Equation 1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Recall is the number of true positives in the proposed model, which is given in Equation 2.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

TABLE II: Results of the Proposed Model

Algorithm	Precision	F1 - Score	Recall	Accuracy
Logistic Regression	Glaucoma - 0.71 Normal - 0.91	0.86	Glaucoma - 0.83 Normal - 0.83	0.83
K Nearest Neighbor	Glaucoma - 0.83 Normal - 0.92	0.91	**Glaucoma - 0.83** **Normal - 0.92**	**0.88**
Support Vector Machine	Glaucoma - 0.62 Normal - 0.90	0.81	Glaucoma - 0.83 Normal - 0.75	0.77
Naive Bayes	Glaucoma - 0.50 Normal - 0.71	0.76	Glaucoma - 0.33 Normal - 0.83	0.66
Decision Tree	Glaucoma - 0.6 Normal - 1.0	0.80	Glaucoma - 1.0 Normal - 0.6	0.77

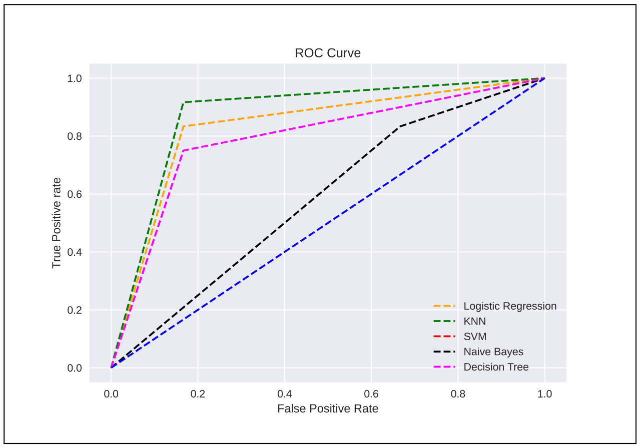

Fig. 5: ROC-AUC for different classifiers

Table II, gives the overall results obtained from various machine learning algorithms. The k-nearest neighbor algorithm gives better results for our data set with both recall and accuracy greater than 80%.

The Receiver Operator Characteristic (ROC) curve is an evaluation metric for binary classification problems. The ROC curve is summarised using the Area Under the Curve (AUC), which measures a classifier's capacity to differentiate between classes. The performance of the model in differentiating between the positive and negative classes improves with increasing AUC.

From Fig. 5 we can conclude that the AUC is higher for the KNN algorithm. The logistic Regression algorithm has the second highest AUC. The ROC-AUC curves obtained are in accordance with the results obtained from various Machine Learning Classifiers Table II.

The observations and inferences obtained from different visualization plots are discussed below. All of the plots are related to the gaze position of the participants. The Trial ID or Image ID refers to the stimuli used for a particular task.

From Fig. 6 and Fig. 7 it can be inferred that the normal participant (indicated using Green Colour) showed fewer fluctuations in their gaze path. For Glaucoma-affected participants (indicated using Violet Colour), the fluctuation in their gaze pattern is large. Fluctuations are represented in red dotted lines.

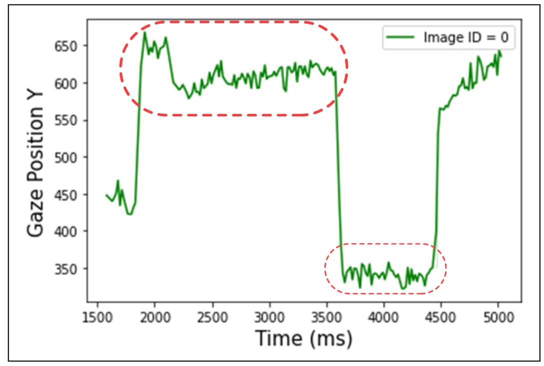

Fig. 6: Gaze Path Trend of Normal Participant for Trial ID 0

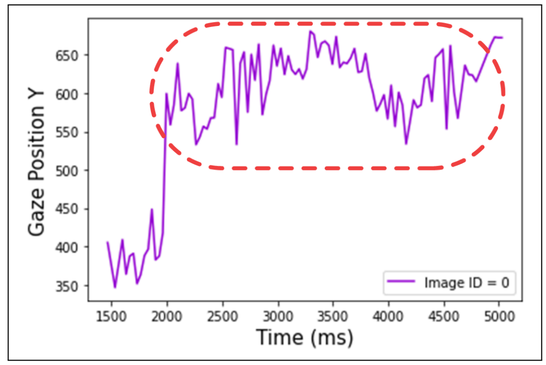

Fig. 7: Gaze Path Trend of Glaucoma Affected Participant for Trial ID 0

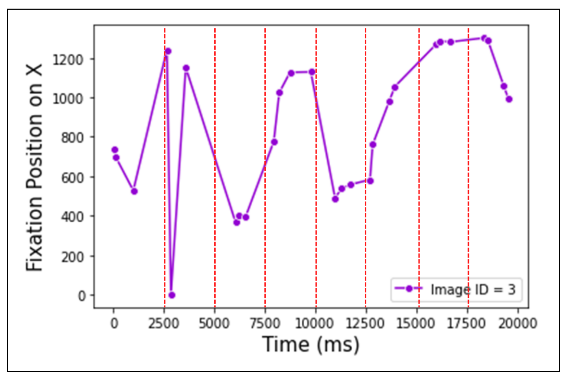

Fig. 8: Horizontal Fixation Count of Glaucoma Affected Participant for Trial ID 3

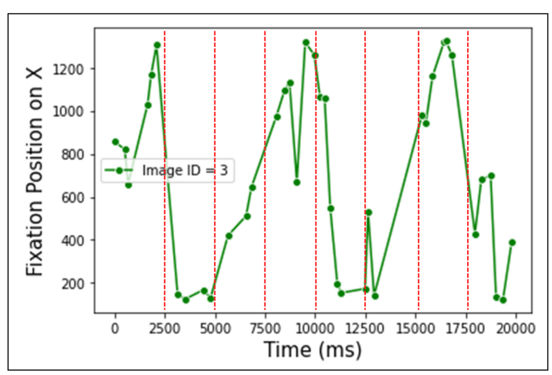

Fig. 9: Horizontal Fixation Count of Normal Participant for Trial ID 3

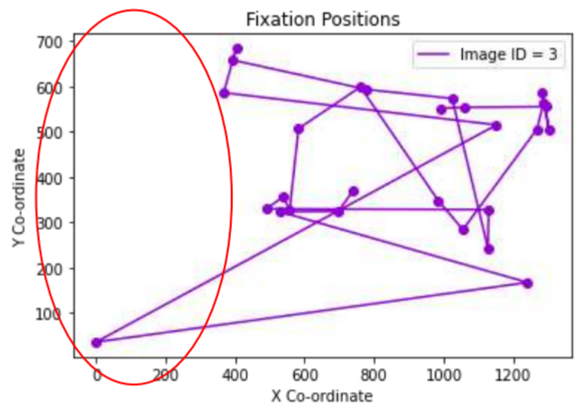

Fig. 10: Trace Path of Glaucoma Affected Participant for Trial ID 3

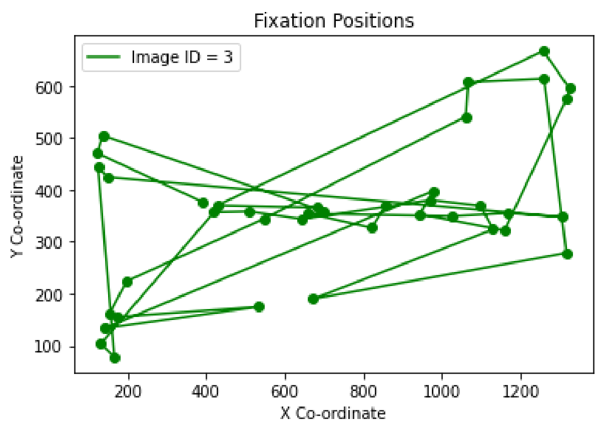

Fig. 11: Trace Path of Normal Participant for Trial ID 3

Fig. 8, Fig. 9 depicted inferences about the gaze path of different participants during different screen-based tasks. Glaucoma-affected participants have a lesser amount of fixation points than the Normal Participants. So, we can conclude that normal participants tend to have more fixation positions than the Glaucoma-affected participant. Similar results were found for Vertical Fixation Positions.

From Fig. 10 the gaze path is mostly towards the right side of the image. The participant is not able to explore more of the red circled part i.e the left portion of the screen while performing a task. The participant affected with Glaucoma has a gaze path that is restricted in a certain way. Fig. 11 showed the gaze path of the normal participant. The gaze path covers almost all portions of the image, i.e no restrictions.

Microsoft PowerBI Software has been used to create an interactive dashboard that highlights fixation length and key influencers which helps to understand how the participants engaged during screen-based tasks. The software summarizes the following inferences.

From Fig. 12, we can observe that the normal participants are in general have a longer fixation length, than glaucoma-

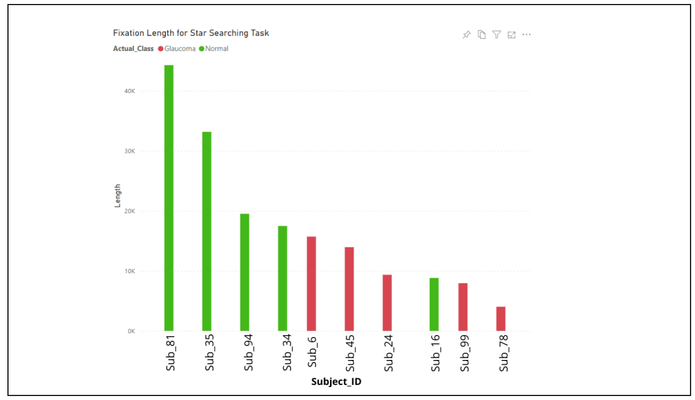

Fig. 12: Fixation Length of Different Participants

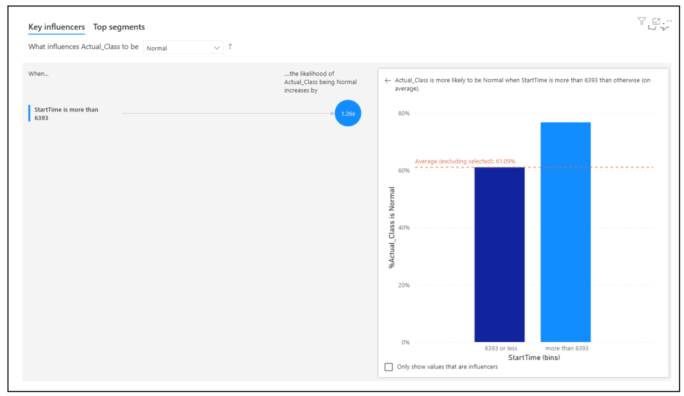

Fig. 13: Key Influencer of Normal Participant based on Start Time

affected participants. The Subject Id_16, can be said as an outlier. The reason for Sub Id_16 being an outlier is that the particular participant stuck only to the goal of finding the hidden object in the image and did not explore the image after finding the hidden object. Whereas the other participants of the Normal class have also explored the image in addition to finding the hidden object. Hence, the normal participant in general has a longer fixation length, whereas Sub Id_16 has a shorter one.

From Fig. 13, we can infer that a normal participant is more likely to have a Start Time greater than 6.3 seconds. The reason behind this inference is that, when displayed with an image for visual search, let's say that normal-class people can find the hidden object. Hence, when displayed with a series of images to find the hidden object, the normal class participant is calm and composed and started the fixation in a slow manner, which according to the key influencer is the normal class participants tend to have a start time greater than 6.3 seconds.

Similarly, the Glaucoma class participant was found to have a Start Time lesser than 6.3 seconds. The reason behind this can be that the glaucoma affected participant was not able to find the hidden object in the image. so, the general tendency of the glaucoma-affected participant is to start the

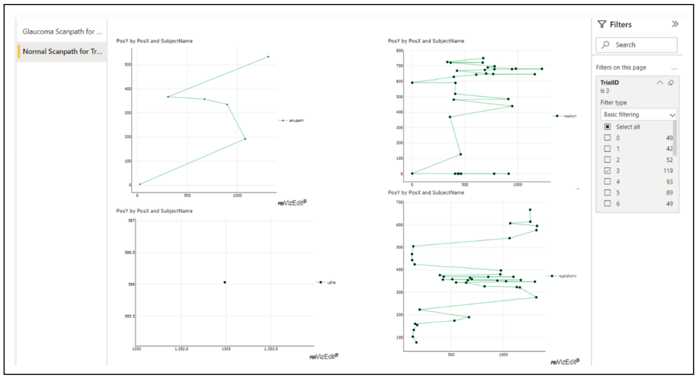

Fig. 14: Interactive Dashboard Created using PowerBI Software

task immediately when an image is displayed. The same conclusion according to the key influencer is the glaucoma class participants tend to have a start time lesser than 6.3 seconds, i.e the participants start the fixation immediately after displaying an image.

A glimpse of the interactive dashboard is given in Fig. 14. The gaze path trend for both normal and glaucoma participant for different trial Id's can be interactively viewed on a single page using the filter option available in the dashboard.

IV. Conclusion

Visualization based on gaze path highlighted the differences between gaze patterns of glaucoma-affected participants and normal participants. Glaucoma showed less number of fixa tion positions than normal participants. The gaze patterns of glaucoma participants during the image search task showed that a large number of fluctuations happened in their eye movements and that they are not able to fixate during the tasks.The novelty of this work lies in the fact that here we can classify participants into glaucoma and normal in terms of visualization using the gaze features obtained from various tasks. From the various plots above it is very clear that the gaze patterns of glaucoma-affected participants vary from the normal participant. The future scope of this paper includes obtaining eye tracking data from more number of participants and visualization of derived features.

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