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RESEARCH ARTICLE

VIS-iTrack: Visual Intention Through Gaze Tracking Using Low-Cost Webcam

SHAHED ANZARUS SABAB[1,2], MOHAMMAD RIDWAN KABIR[1,2], SAYED RIZBAN HUSSAIN[1,2], HASAN MAHMUD[1,2], HUSNE ARA RUBAIYEAT[3], AND MD. KAMRUL HASAN[1,2]

[1]Systems and Software Laboratory (SSL), Islamic University of Technology (IUT), Gazipur 1704, Bangladesh
[2]Department of Computer Science and Engineering, Islamic University of Technology (IUT), Gazipur 1704, Bangladesh
[3]Natural Science Group, National University, Bangladesh, Gazipur 1704, Bangladesh

Corresponding author: Mohammad Ridwan Kabir (ridwankabir@iut-dhaka.edu)

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by IUT-REASP.

ABSTRACT Human intention is an internal, mental characterization for acquiring desired information. From interactive interfaces containing either *textual* or *graphical* information, intention to perceive desired information is subjective and strongly connected with eye gaze. In this work, we determine such intention by analyzing real-time eye gaze data with a low-cost regular webcam. We extracted unique features (e.g., *Fixation Count, Eye Movement Ratio*) from the eye gaze data of 31 participants to generate a dataset containing 124 samples of visual intention for perceiving *textual* or *graphical* information, labeled as either *TEXT* or *IMAGE*, having 48.39% and 51.61% distribution, respectively. Using this dataset, we analyzed 5 classifiers, including *Support Vector Machine* (*SVM*) (*Accuracy*: 92.19%). Using the trained *SVM*, we investigated the variation of visual intention among 30 participants, distributed in 3 age groups, and found out that young users were more leaned towards *graphical* contents whereas older adults felt more interested in *textual* ones. This finding suggests that real-time eye gaze data can be a potential source of identifying visual intention, analyzing which intention aware interactive interfaces can be designed and developed to facilitate human cognition.

INDEX TERMS Human-computer interaction, visual intention detection, eye gaze, Kalman filtering, saccades, fixation, support vector machine, intention aware interfaces.

I. INTRODUCTION

Human cognition processes, such as thinking, learning, remembrance, decision-making comprise a significant part of Human-Computer Interaction (HCI). These processes lead to intentions that are implicit in nature and cannot be easily interpreted [1]. So far, researchers have tried to determine such intentions in different scenarios of HCI [1]–[6] using eye gaze data. The eye movement patterns vary across different implicit intentions. The *saccadic* and *fixation* movements of the human eyes are vital to the determination of user intention [7]. During the *saccadic* movement, both of our eyes move simultaneously and quickly between two points in the visual field without collecting much useful information [7], [8]. However, during *fixation*, occurring between two *saccadic* movements, the human eyes tend to focus on a certain *Region of Interest* (*ROI*) in the corresponding visual field, typically for a period of 200-600ms [7]–[9] known as the *fixation duration*, where perception occurs.

Information on interactive interfaces is usually presented in two modes, either *textually* or *graphically*, on a computer screen. The intention to retrieve *textual* or *graphical* information from such interfaces is a human cognitive process that is implicit in nature [8]. Therefore, analyzing the *saccadic* and *fixation* movements of the human eyes while interacting with such interfaces, recorded with different eye-tracking technologies, can create a pathway for determining the visual intention of a user to retrieve information from

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a particular type of content. The human intention varies within different groups i.e., demographics, gender [10], and age [8]. Due to this subjective behavior, the *User Interface* (*UI*) or *User Experience* (*UX*) designers can present relevant information based on different types of applications targeted towards different user groups. Therefore, analysis of users' gaze information through features such as *eye movement time*, *fixation time*, and *jerky movement time* is subjected to be a viable option for detecting users' intention and their goal formulation process [3], [11]–[14].

In this work, we present a system to detect and classify human intentions to perceive *textual* or *graphical* information from interactive interfaces through classical *Machine Learning* (*ML*) approach based on real-time eye movement tracking using a low-cost general-purpose webcam. Leveraging the eye-tracking strategies using such webcams, reported in studies [15]–[18], we developed our tracking system using the webcam feed as a reference. In our approach, we have extracted the pupil coordinates of the user's eyes while they are focusing on a particular section of the screen. We have improved the eye detection by adding heuristic calculation [19] of the relative eye regions and only considered small region (where eyes can reside) to remove noises. Furthermore, to increase classification accuracy, we have smoothened the *pupil movement path* using the Kalman filter [20].

Our aim is to perform a case study where we extract key features from user's gaze data and analyze its impact on the *binary classification* of users' focus on either *textual* or *graphical* information presented on a computer screen. Therefore, we have explored 5 classifiers such as *K- Nearest Neighbors* (*KNN*), *Gaussian Naïve Bayes* (*GNB*), *Logistic Regression* (*LR*), *Support Vectors Machine* (*SVM*), and *Random Forest* (*RF*) to get an understanding of the type of classifier that is reliable for relevant studies.

Since we have processed real-time video feed from the webcam at *30 frames per second* (*fps*), each frame needs to be processed individually for tracking the user's gaze. Therefore, to ensure real-time eye gaze detection, we need to reduce the computational cost while maximizing the performance of the classifiers. This can be achieved with a minimalistic feature vector containing only the vital features. Therefore, we have defined a *feature vector* containing 8 features (4 features unique to each eye), using which we have generated a dataset to train and test the classifiers through *Repeated K-Stratified Fold Cross-Validation* [21] with K=10 fold and 5 repetitions. The classifiers are evaluated using different metrics such as the *Accuracy*, *Area Under the ROC Curve* (*AUC*), *Precision*, *Recall*, and *F1-score*.

As the movement of our eyes are coordinated, we cannot move them individually, in different directions. Again, due to binocular vision, we cannot perceive information from two different visual stimuli, one placed in front of each eye, simultaneously [22]. Therefore, while focusing on a visual stimulus, the eye movement paths vary for both eyes. We investigated the performance of the classifier having features from a single eye (left) vs both eyes. Our result suggests that the performance is better while using features from both eyes (details in Section 3.7).

Furthermore, to showcase one application of our technique, we conducted a user study where we determined the type of information that was focused on more (*textual* or *graphical*) across different age groups using *SVM* as a trained classifier. We have adopted SVM due to different factors such as – 1) Having the highest performance while trained with the features from both eyes (*Accuracy:* 92.19%), 2) Faster inferencing time (i.e., avg inference time = 0.8 milliseconds/sample), 3) With a comparatively smaller dataset, SVM is less vulnerable to overfitting, favoring generalization [23]. A brief overview of our proposed approach of determining visual intention is shown in Fig. 1.

To summarize our contributions: 1) We develop a feature extraction system, which takes real-time gaze information for feature engineering. 2) We verify that a machine learning model, leveraging the gaze features can be used in classifying visual intention (TEXT vs IMAGE), and 3) We demonstrate one application of visual intention to present adaptive user-interface to users of different age groups.

In the next section, we present the literature review followed by an explanation of the proposed approach of determining the visual intention of a user to retrieve *textual* or *graphical* information from interactive interfaces. We then elaborate on the user study and analyze the outcomes of the study. Finally, we summarize our observations and give a direction on future works.

II. RELATED WORKS

The human eyes are sources of rich visual information and can provide an insight of the human intention through analysis of their eye gaze data. This is an emerging field of research where several studies have been conducted to date.

Pupil detection and tracking is a vital and the most difficult step for eye gaze tracking [15]. In order to accomplish this, researchers in this domain have used eye-trackers such as RED Eye-tracker [24], ASL 504 [8], Tobii [1], [2] or other head-mounted devices for extracting different features such as *pupil size variation*, *eye scan path*, *saccades*, *fixation*, and *ROIs* [1], [2]. However, these devices are costly, making such systems infeasible and inaccessible to the general mass. To resolve these shortcomings, studies [15]–[18] have analyzed the feasibility of tracking eye gaze using low-cost regular webcams such as Logitech C300 [15], Logitech Quick Cam Pro 9000 [17] in real-time with reasonable accuracy, resulting in a cost-efficient solution and eliminating the burden of a head-mounted device. Using *Circular Hough Transform* (*CHT*) [25], [26], eye pupils have been tracked using such webcams after processing the camera feed in [15]. Researchers have also explored neural networks for eye gaze tracking due to its robustness to noisy data [16]. A comparative analysis of different algorithms such as *Cumulative Distribution Function* (*CDF*), *Projection Function* (*PF*), *Edge Analysis* (*EA*) have also been carried out to understand

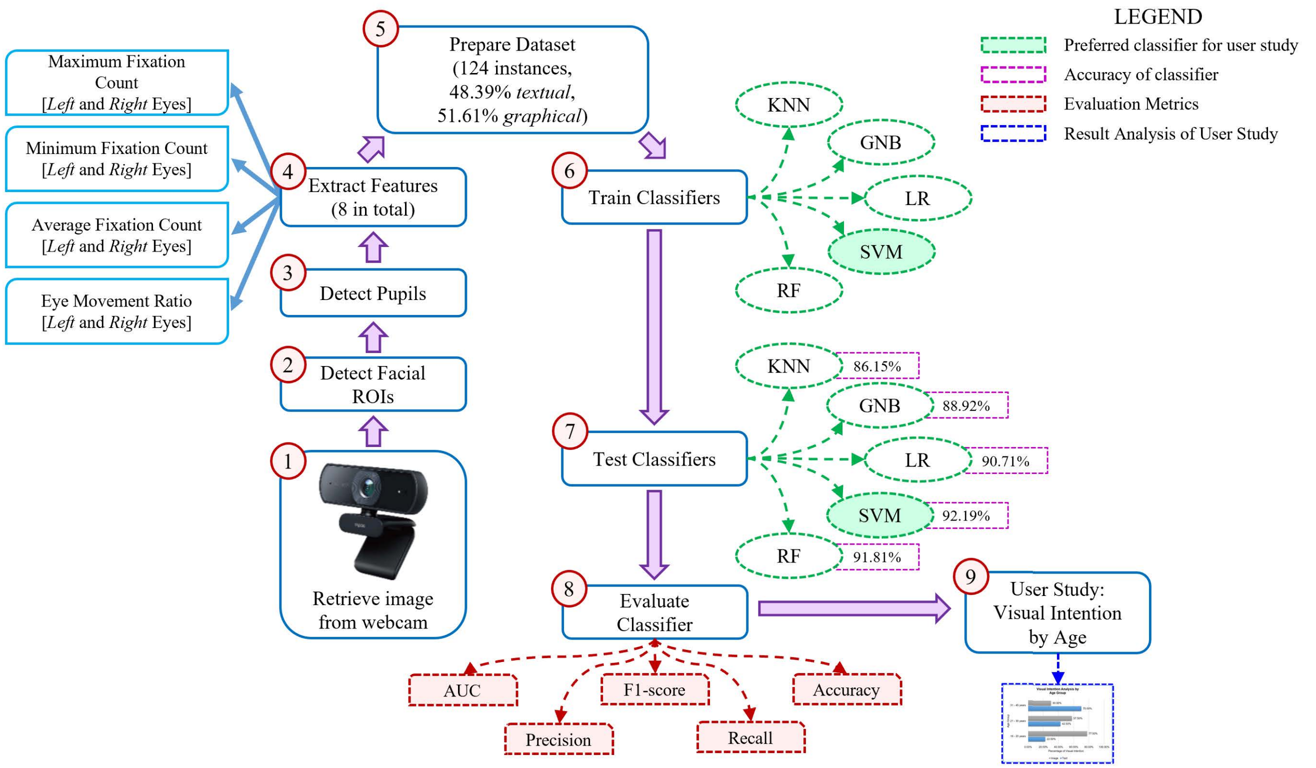


FIGURE 1. Overview of the proposed approach of determining visual intention for textual or graphical contents in interactive interfaces.

the type of pupil detection approach best suited for regular webcams [18]. Motivated by the previous works, we chose to work with a low-cost regular webcam for eye gaze tracking, providing a cost-effective solution to visual intention detection.

Researchers in [1] have attempted to classify implicit human intention as either *navigational* or *informational* in both indoor and outdoor environments. They have extracted key features of the eye such as *fixation length*, *fixation count*, and *pupil size variation* as reliable features from eye gaze data, recorded using the Tobii 1750 eye-tracker. They have used two types of classifiers: (1) *Nearest Neighborhood* (*NN*) and (2) *SVM*. The average accuracy of the proposed system considering these two classifiers was over 85%. The major drawback of their recommended architecture is the dependency on an expensive eye-tracking system. Apart from identifying human intention as *navigational* or *informational*, a new type of intention, *transactional*, has also been explored in case of web searching [4] through analysis of a web search engine log containing about a million and a half queries from numerous hundred thousand users. The authors have developed an automated three level classifier with features such as *Color Histogram, Color Spread,* and so on. The reported accuracy of their approach was 74%. However, there are a few limitations of this study, as stated by the authors themselves. First, the user intent for a particular query was annotated to single search intent (*informational, navigational,* or *transactional*), manually from the search engine log whereas a particular search may have multiple possible intention due to the implicit and hard to interpret nature of human intentions. Second, there is an inherent shortcoming of relying solely on data from transaction logs, which involves not having access to the users for correctly identifying their intent. The accuracy of their classifier is valid given that the manual classification of queries is correct. However, the stated accuracy of their classifier over such a large dataset is an indication of its robustness. In other research works [5], having similar classification objectives as [1] and [4], user queries were manually classified from a relatively smaller transaction log for gaining an insight into the proportions of various types of search intents of the users. Findings of these studies suggest that about 40% of such intentions were *informational*. However, one limitation of [5] is that it was not verifiable whether the manual classifications of intents were in fact, the original intent of the user. Considering these research works, we have considered fixations and eye movement patterns as relevant features from gaze information.

With reference to the previous works, devices such as RED Eye-tracker [24], ASL 504 [8], Tobii [1], [2] seem to be viable alternatives to pupil tracking. However, compared to a regular webcam, different factors such as – availability, accessibility, and affordability of these devices make them unpragmatic for regular usage, which motivated us to choose regular webcams for our research purpose. Feature extraction in real-time

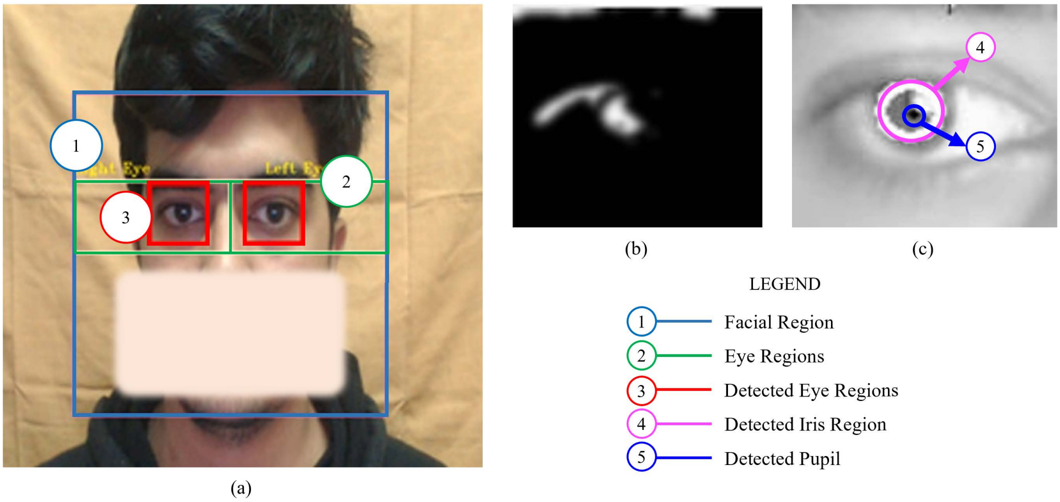
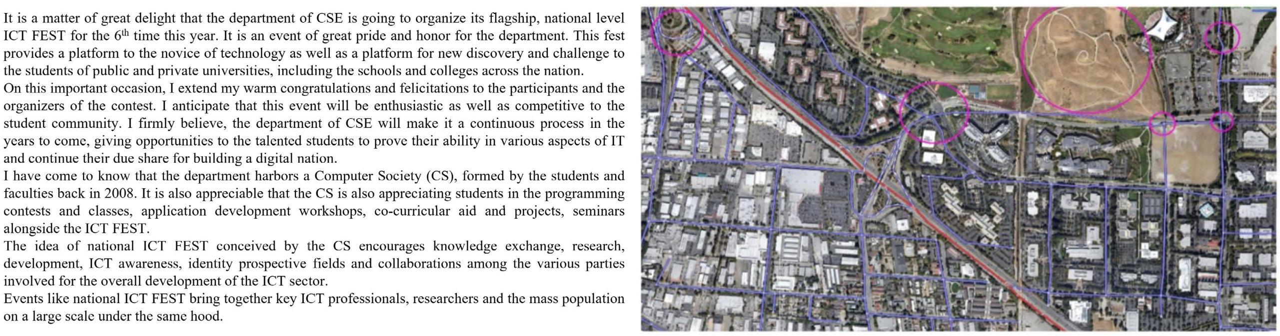


FIGURE 2. **(a) Facial and Eye Regions of a user. (b) Detected and processed Right eye for iris and pupil detection. (c) Detected Iris Region and Pupil of the Right eye.**



It is a matter of great delight that the department of CSE is going to organize its flagship, national level ICT FEST for the 6th time this year. It is an event of great pride and honor for the department. This fest provides a platform to the novice of technology as well as a platform for new discovery and challenge to the students of public and private universities, including the schools and colleges across the nation.
On this important occasion, I extend my warm congratulations and felicitations to the participants and the organizers of the contest. I anticipate that this event will be enthusiastic as well as competitive to the student community. I firmly believe, the department of CSE will make it a continuous process in the years to come, giving opportunities to the talented students to prove their ability in various aspects of IT and continue their due share for building a digital nation.
I have come to know that the department harbors a Computer Society (CS), formed by the students and faculties back in 2008. It is also appreciable that the CS is also appreciating students in the programming contests and classes, application development workshops, co-curricular aid and projects, seminars alongside the ICT FEST.
The idea of national ICT FEST conceived by the CS encourages knowledge exchange, research, development, ICT awareness, identity prospective fields and collaborations among the various parties involved for the overall development of the ICT sector.
Events like national ICT FEST bring together key ICT professionals, researchers and the mass population on a large scale under the same hood.

FIGURE 3. **Sample images with textual (left) and graphical (right) contents used for dataset generation.**

from a webcam is highly dependent on the unobtrusive pupil tracking approach. Earlier works found promising results in finding pupil area using *Circular Hough Transform* (*CHT*) [15], [30], [31], and therefore, we adapted this technique for pupil tracking. To further improve the performance of such approach, the input image (eye image) that has been fed into CHT plays a vital role. In this regard, we applied a modified heuristic calculation [19] to find out the relative eye areas, followed by the Viola-Jones algorithm [32]–[35] to find out the images of the left and the right eyes in real-time, which are then fed into the CHT to find out respective pupils.

Pupil occlusion during eye blinks poses another challenge for real-time pupil tracking, in which cases we applied Kalman filtering [20] to approximate the relative eye pupil coordinates. More importantly, investigating into the efficacy of features for exploring human intent, we discovered that fixation and saccadic eye movements [1], [2] proved to be more adaptable than features, such as – Color Histogram, Color Spread and User logs [4], [5]. Hence, we have developed our feature sets using eye fixation durations and saccadic movements.

In the next section, we discuss our proposed approach, where we try to determine the visual intention of a user to retrieve *textual* or *graphical* content from interactive interfaces.

III. PROPOSED APPROACH

In this section, we elaborate on our proposed approach of processing the webcam feed for *face detection* and outlining the eye regions. Once the left and the right eye regions are detected, they are processed for *iris and pupil detection,* followed by *pupil tracking*. Next, we discuss feature extraction, dataset generation and analysis of feature properties. Finally, we present our approach of classifying visual intention followed by the evaluation of classifier performance.

A. WEBCAM IMAGE PROCESSING

Our motivation behind using a generic webcam (*Logitech C920*) is to develop a cost-efficient solution for determining visual intention using users' gaze. One of the challenges of this study is to track the movement of the eye pupils using the low-resolution *Real-Time Video Feed* (*RTVF*) of the webcam [15]. For our purpose, we have used an image resolution of 800×600 at 30 fps. For pupil tracking, we have followed a six-step process. The steps are: (1) Regions containing the viewer's face (Fig. 2a, *Legend:* "*Facial Region*") is detected in real-time using the *Viola-Jones* [32]–[35] algorithm, facilitating rapid face detection, which is an essential aspect of our proposed approach. We have used a pretrained Haar-Cascade face detection model based on the sample dataset [36], containing thousands of negative and positive facial image information. At the beginning of each user session, a calibration phase is required, where the *RTVF* is processed for manual tuning of image-related parameters (min-max object size, min neighbors, etc.) [37] until viewer's face is detected. The calibration is essential because of how light reflects differently for people with different skin tones. (2) The probable eye regions (Fig. 2a, *Legend:* "*Eye Regions*"), are identified using a modified heuristic calculation based on [19]. (3) The *left* and the *right* eyes are detected from the respective eye regions (Fig. 2a, *Legend:* "*Detected Eye Regions*") in the same approach as face detection, using two separate datasets [38]. Since these eye regions are smaller than that of the face (Fig. 2a, *Legend:* "*Facial Region*"), feature matching in this reduced space enhances the accuracy of eye detection. (4) The detected eyes are further processed to enhance the contrast using Histogram Equalization [39], followed by inversion and binary thresholding, and finally, transformation using *Gaussian Pyramid* [40]. For instance, Fig. 2b shows the processed image of the right eye. (5) From the processed image of each eye, the *iris* region is detected using *CHT* [25], [26], and the *pupil* is considered as the center of this region. For example, the detected *iris* region and the *pupil* are outlined for the right eye in Fig. 2c. (6) Although the pupils are calculated as the center of the iris, misdetections were observed in some frames at 30 fps. Potential reasons for such misdetections could be the occlusion of the iris and the pupils during eye blinks. This situation is undesired; therefore, we have introduced *Kalman* filter [20] in the pipeline, drastically reducing such cases. The coordinates of the pupils are then recorded for tracking their movements.

B. FEATURE EXTRACTION

Eye gaze and its variations are mere considerations of the pupil movement and its variation, respectively. Distinguishable characteristics of pupil movement are noted from various contexts, which help in the determination of users' intention. After the pupils of both eyes have been tracked down, the next step is to extract unique features for classifying an intention to be either focused on *textual* or *graphical* contents. An important point to note is that since we are detecting human intentions using real-time tracking of viewer's gaze using a low-cost webcam, we focused on features that may be sufficient for accurately classifying visual intention with reduced computational complexity. Therefore, we have calculated 4 features such as *Maximum Fixation Count* (*MAX_FC*), *Minimum Fixation Count* (*MIN_FC*), *Average Fixation Count* (*AVG_FC*), and *Movement Ratio* (*MR*), for both *Left* (*L*) and *Right* (*R*) eyes, resulting in a total of 8 features for training the classifiers.

1) FIXATION COUNT

Gaze points detected using an eye-tracking system give an idea of a viewer's interest. When a collection of gaze points is very close to each other, a viewer is said to have fixated his/her focus on that *ROI*, containing the collection of gaze points. *Fixation duration*, defined as the amount of time spent on a particular *ROI*, is considered to be one of the most useful features for determining visual intention in the area of eye-tracking research [41], [42]. *Fixation Count* (*FC*) is defined as the number of gaze points in a particular *ROI*. The previous studies [43], [44] have shown that the *fixation duration* is longer when a user is looking at *graphical* content compared to *textual* ones. *Graphical* information includes *discrete* points of focus, whereas; *textual* information includes *continuous* points of focus. Based on prior studies [8], [12], [27], [28], [45], we considered *fixation duration* of 200ms as a threshold to define a fixation event. Intuitively, the *fixation counts* also increase proportionally with *fixation duration*. Based on these observations, in our study, we have calculated the *Minimum, Maximum,* and *Average Fixation Counts* for each of the eyes, resulting in 6 features for training the classifiers.

2) EYE MOVEMENT RATIO

Apart from *fixation counts*, another distinguishable feature for intention detection is the *Movement Ratio* (*MR*) that depends on the *horizontal* and the *vertical* scan counts of an eye, as shown in (1).

$$Movement\ Ratio = \frac{Count\ of\ Horizontal\ Scans}{Count\ of\ Vertical\ scans} \tag{1}$$

This feature is vital for determining such visual intentions, because, when the visual stimulus is *textual*, we observed that the horizontal movement of the eye is greater than its vertical movement [12], [45] whereas, for *graphical* information, both of these movements are of similar proportions [24]. Therefore, this ratio appears to be higher for *textual* information than that for *graphical* information. In our study, we have considered the *MR* of both eyes, resulting in 2 more and a total of 8 features for training the classifiers.

C. DATASET GENERATION

For preparing the dataset, 31 participants (Mean: 28.32 years, SD: 10.30 years, Male: 66.67%, Female: 33.33%) were recruited (i.e., via social media and word of mouth) for going through multiple images of *textual* and *graphical* contents. We considered a collection of 20 contents, consisting of 10 textual and 10 graphical ones. The word count in the *textual* contents ranged between 200 and 500, and the *graphical* contents involved images with several highlights. As, for our investigation, we chose to work with contents having an aspect ratio 4:3 and 16:9 because of the widespread usage in the media. From each collection of contents, each participant

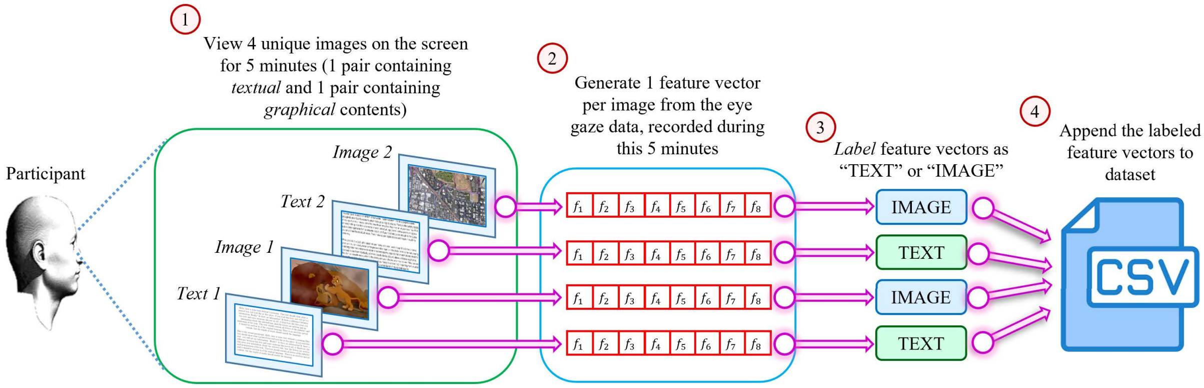


FIGURE 4. Workflow diagram of generating dataset from eye gaze.

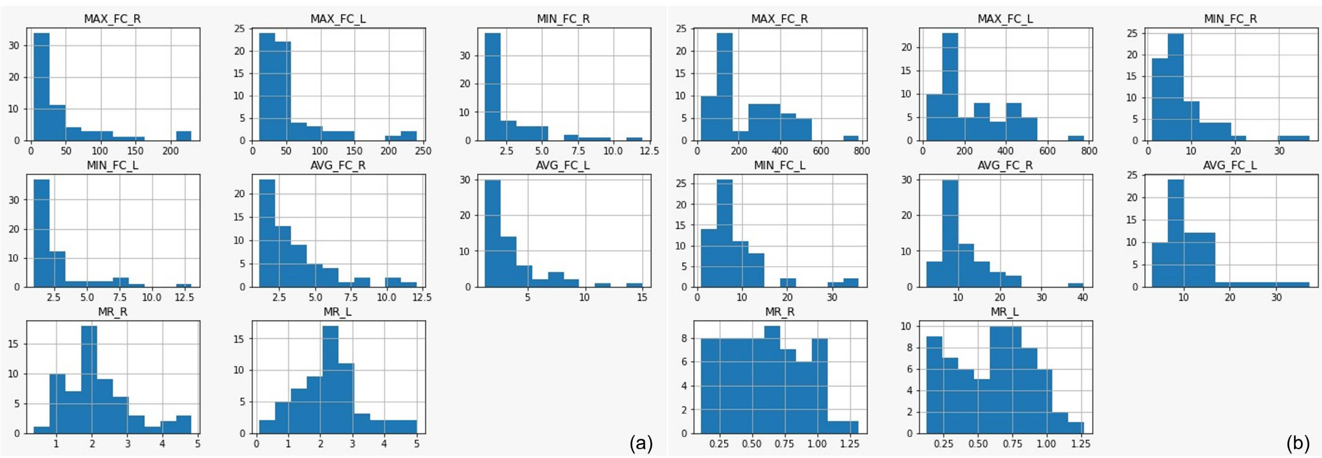


FIGURE 5. Feature Histogram-plot (FH-plot) of (a) textual and (b) graphical contents, where for each feature, the x-axis represents the range of values, and the y-axis represents the frequency of the values in a particular range.

TABLE 1. Summary of the dataset prepared for the study.

Property	Value
Total Instances	124
Number of Features	8
Class Labels	"TEXT" "IMAGE"
Class Distribution	"TEXT" – 48.39% "IMAGE" – 51.61%

was asked to go through 2 randomly chosen unique *textual* and 2 randomly chosen unique *graphical* contents. Before initiating sample collection each participant was instructed about the task followed by a trial session which combinedly took roughly ∼10 minutes. The trial session was introduced to give an essence of the real task and no data was recorded during this period. A pair of our sample contents used for dataset generation is shown in Fig. 3.

During the sample collection, each participant was given 5 minutes per content, while eye gaze data were recorded, analyzed, and the corresponding feature vector was generated. Therefore, for 4 contents each participant was given in total of 20 minutes. At the end of the experiment, the dataset, containing 124 feature vectors (*31 participants* × *4 contents per participant*) as instances, was prepared. A workflow diagram of dataset generation is outlined in Fig. 4. Furthermore, since we used a regular webcam without infrared capability, sufficient lighting condition was ensured for proper data collection. A summary of the dataset is provided in Table 1 and an extract from the dataset is given in Table 2.

D. FEATURE PROPERTY ANALYSIS

From the *Feature Histogram-plot* (*FH-plot*) in Fig. 5, where for each feature, the x-axis represents the range of values, and the y-axis represents the frequency of the values in a particular range, it is evident that the *Average Fixation Count* (*AVG_FC*) of both *Left* (*L*) and *Right* (*R*) eyes for *graphical* (images) contents (Fig. 5a) is very high (5 – 10) compared to the *textual* ones (0 – 2.5) (Fig. 5b). The reason for such high

TABLE 2. Extracted features from 10 samples of our dataset.

Features								Label
MAX_FC_R	*MAX_FC_L*	*MIN_FC_R*	*MIN_FC_L*	*AVG_FC_R*	*AVG_FC_L*	*MR_R*	*MR_L*	
37	45	2	1	3.115	2.272	2.385	2.04	TEXT
363	392	7	3	11.274	8.318	0.227	0.374	IMAGE
119	113	5	6	23.462	26.857	1.066	0.758	IMAGE
17	30	2	2	2.175	2.635	1.894	2.147	TEXT
13	29	2	1	2.102	1.937	1.68	2.157	TEXT
478	485	9	12	10.23	15.69	0.221	0.361	IMAGE
111	107	1	1	9.781	8.271	0.993	0.887	IMAGE
413	421	4	4	12.974	11.883	0.653	0.652	IMAGE
221	241	4	2	5.456	5.287	1.112	1.037	TEXT
521	518	15	13	18.641	14.391	0.576	0.489	IMAGE

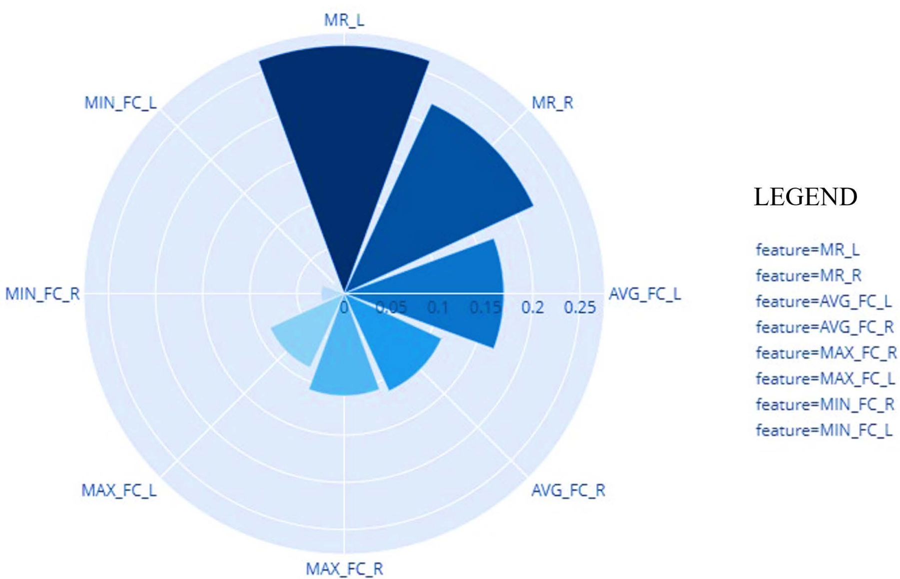


FIGURE 6. Feature Importance-plot (FI-plot) using Gini impurity, summarizing the relative importance of the proposed features for classifying visual intention for retrieving textual or graphical information based on eye gaze data. Movement Ratio (MR) of the eyes are the most vital ones, followed by the Average Fixation Count (AVG_FC) for such classification.

values is that people tend to retrieve information from isolated points [7], [8], [11], [24] from images. Therefore, a greater amount of focus on discrete points increases the fixation count for *graphical* information. Another distinguishable feature is the *Movement Ratio* (*MR*) of the eyes because while retrieving any textual information, a user normally reads from left to right. As a result, the horizontal movement of the eyes dominates the vertical movement [12], [45] and the value of this ratio increases. It can be seen from the *FH-plot* (Fig. 5) that for *textual* contents (Fig. 5a) this ratio is normally distributed within the range of 1 to 5, whereas, for *graphical* contents (Fig. 5b) the value of this ratio ranges between 0 to 1, distributed uniformly. Therefore, a high value of this ratio clearly points to the class of *textual* contents. Based on these observations, *Movement Ratio* (*MR*) of the eyes appear to be the most vital feature, succeeded by *Average Fixation Count* (*AVG_FC*), for classifying visual intention for retrieving *textual* or *graphical* content.

E. CLASSIFICATION

Our objective is to build a reliable approach of classifying visual intentions based on textual or graphical contents using eye gaze data. Therefore, we adopted a systematic approach of investigating 5 different classifiers such as *K-Neighbors Classifier* (*KNN*), *Gaussian Naïve Bayes* (*NB*), *Logistic Regression* (*LR*), *Support Vectors Machine* (*SVM*), and *Random Forest* (*RF*) to justify which classifier works well with this kind of data.

For KNN, we chose 5 neighbors, with the distance metric as '*minkowski*', while ensuring uniform weight distribution to all the neighbors. We have used '*liblinear*' solver [46], [47] for *LR* in combination with an '*L2*' penalty. Considering the

TABLE 3. Grid search space of the hyper-parameter optimization.

ML Model	Hyper-parameter	Search Space	Selected Value
	n_neighbors	[3, **5**, 11, 20]	**5**
KNN	*metric*	[‘***minkowski***’, ‘*euclidean*’, ‘*manhattan*’]	***minkowski***
	weights	[‘***uniform***’, ‘*distance*’]	***uniform***
	solver	[‘*newton-cg*’, ‘*lbfgs*’, ‘***liblinear***’]	***liblinear***
LR	*penalty*	[‘*none*’, ‘*L1*’, ‘***L2***’, ‘*elasticnet*’]	***L2***
	C	[0.001, 0.01, 0.1, **1**, 10, 100]	**1**
	n_estimators	[50, 100, **200**, 300, 500]	**200**
RF	*max_features*	[‘*auto*’, ‘***sqrt***’, ‘*log2*’]	***sqrt***
	max_depth	[4, **5**, 6, 7, 8]	**5**
	criterion	[‘***gini***’, ‘*entropy*’]	***gini***
	C	[0.1, **1**, 10, 100]	**1**
SVM	*kernel*	[‘*rbf*’, ‘***linear***’, ‘*sigmoid*’]	***linear***
	gamma	[0.01, **0.1**, 1]	**0.1**

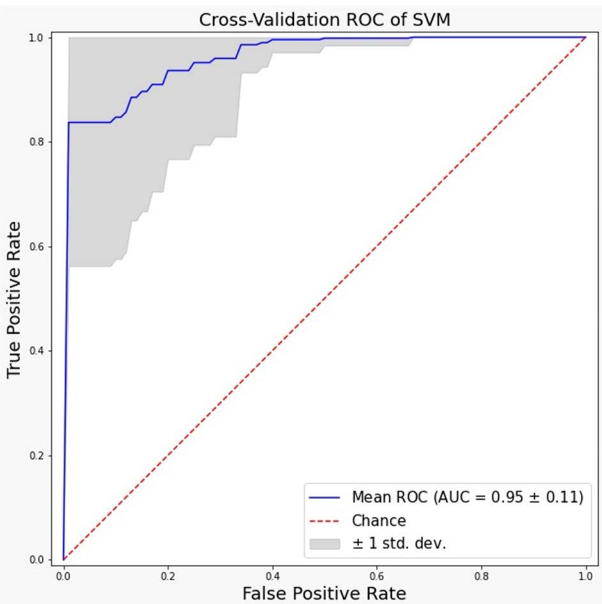


FIGURE 7. Receiver Operating Characteristic (ROC) curve for SVM.

case of SVM, we used ‘*linear*’ kernel, where the values of ‘*gamma*’ and ‘*C*’ were set to 0.1 and 1.0, respectively. Here, ‘*gamma*’ and ‘*C*’ are called the Kernel coefficient and the regularization parameter, respectively. For RF, involving 200 trees, the value of the parameter, ‘*max_features*’ was selected as the squared root of the total features, while calculating the quality of split using ‘*Gini*’ impurity [48] and restricting the maximum depth of the trees to 5. The hyper-parameters of the classifiers were optimized using Grid Search [49] and their corresponding search space is reported in Table 3. Considering the small volume of the generated dataset, the classifiers were trained and tested following supervised learning methodology with *Repeated K-Stratified Fold Cross-Validation* [21] with K=10 and 5 repetitions.

F. FEATURE IMPORTANCE ANALYSIS

In order to perceive the relative importance of the proposed features on the classification of visual intention from eye gaze data, we calculated their Gini impurities [48], using *RF*. For a particular feature, as the mean decrease in this impurity increases, the relative importance for that feature also increases. Utilizing this property, we have generated a *Feature Importance-plot* (*FI-plot*) of our proposed feature vector with the mean decrease in impurity plotted along the y-axis, as shown in Fig. 6, summarizing the relative importance of the features for such classification of visual intention. From the analysis of the *FI*-plot, as shown in Fig. 6, we have found that the features – eye *Movement Ratio* (*MR*) and *Average Fixation Count* (*AVG_FC*) are two of the most important features, contributing to the classification of visual intention as *textual* or *graphical* using eye gaze data.

G. CLASSIFIER PERFORMANCE ANALYSIS

After training and testing the classifiers, we have measured their performance using different metrics such as the *Accuracy, Area Under the ROC Curve* (*AUC*), *Precision*, *Recall*, and *F1-score*. From our analysis, we have found *SVM* and *LR* to perform better than the other classifiers.

For any binary classifiers, the *Receiver Operator Characteristic* (*ROC*) curve is a probability curve of the *True Positive Rate* (*TPR*) or “*Sensitivity*”, as in (2) and *False Positive Rate* (*FPR*) or “*1 – Specificity*”, as in (3). This curve essentially differentiates the signal from the noise. *TPR* and *FPR* quantifies the ability of a binary classifier to correctly classify the *positive* and the *negative* classes, respectively. Therefore, a higher value of *TPR* and a lower value of *FPR* is preferred for any binary classifier to be reliable.

$$TPR \text{ or } Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{2}$$

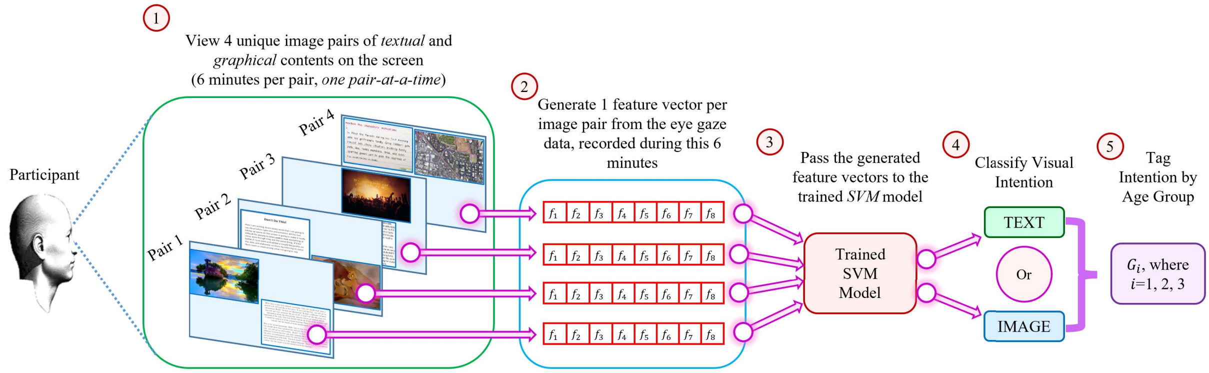


FIGURE 8. Workflow diagram of visual intention detection by age group from eye gaze.

TABLE 4. Evaluation of the classifiers using different metrics.

Features Considered	Classifier	Accuracy (%)	AUC	Precision	Recall	F1-Score	Training Time (ms)	Average Inferencing Time (ms)
Both Eyes	*SVM*[a]	**92.19**	0.9548	**0.9307**	**0.9212**	**0.9206**	34797	1.4720
	RF	91.81	**0.9631**	0.9282	0.9167	0.9163	91146	2.4969
	LR	90.71	0.9546	0.9192	0.9069	0.9054	1253	0.0230
	GNB	88.92	0.9556	0.9010	0.8890	0.8874	543	0.0199
	KNN	86.15	0.9118	0.8798	0.8605	0.8579	799	0.0928
One Eye (Left)	SVM	**89.25**	0.9536	**0.9139**	0.8898	0.8880	18898	0.9299
	RF	88.92	0.9242	0.8997	0.8893	0.8880	76558	2.5051
	LR	89.76	**0.9552**	0.9122	**0.8957**	**0.8945**	617	0.0392
	GNB	88.10	0.9533	0.8919	0.8812	0.8793	513	0.0255
	KNN	85.55	0.9248	0.8736	0.8550	0.8518	688	0.0940

[a] Preferred classifier for the user study in Section IV.

TABLE 5. Demographic details of the 3 age groups considered in the user study.

Age Group (years)	Group Tag	Mean Age (years)	SD (years)	Male Ratio (%)	Female Ratio (%)
16 – 20	G_1	17.80	1.54	70	30
21 – 30	G_2	26.60	4.10	60	40
31 – 45	G_3	37.10	3.99	40	60

$$FPR\ or\ \ (1 - Specificity) = \frac{False\ Positive}{True\ Negative + False\ Positive} \tag{3}$$

The *AUC* quantifies the capability of a binary classifier to distinguish between the classes and is used to summarize the *ROC* curve. *Precision* is the ratio of the *True Positive* classifications out of all the positive predictions (*True Positives* and *False Positives*) and *Recall* is a measure of the percentage of actual *positive* classes that were correctly identified. However, maximizing *Precision* may compromise *Recall* and vice versa. To address this issue, the *F1-Score* is used to combine both *Precision* and *Recall* into a single classifier evaluation metric. Finally, *Accuracy* is the ratio of the correct predictions and the total number of predictions available.

The evaluation results along with the *Training* and the *Average Inferencing* times of each of the classifiers in two scenarios (features from *both eyes* vs *one eye*) are summarized in Table 4, where the model evaluation metrics have higher values, when features from *both eyes* are considered compared to *one eye*. Thus, we opted for considering eye gaze features of both eyes and *SVM* as our preferred classifier for the user study in the next section, as it has the highest *Accuracy* (92.19%) in this case. In addition, the average inferencing time per sample for SVM was 1.47 ms (milliseconds) for both eyes. The cross-validation *ROC* curve of *SVM,* as shown in Fig. 7, summarizes the *ROCs* (within 1 standard deviation) of all folds using *Repeated K-Stratified Fold Cross-Validation* [21] with K=10 and 5 repetitions and features of both eyes, and the blue line indicates the corresponding mean ROC curve.

IV. USER STUDY: VISUAL INTENTION BY AGE

In this section, we elaborate on the user study where we aim to understand how the interest in *textual* or *graphical* information varied across users of different age groups by analyzing their eye gaze data. An analysis of such behavior will help us understand the design principle behind the development of interactive interfaces, targeted towards users of a particular age group, facilitating enhanced HCI. As mentioned earlier, we adopted the trained *SVM* classifier for this experiment.

A. PARTICIPANTS

We recruited 30 participants (Mean: 27.17 years, SD: 8.60 years, Male: 56.67%, Female: 43.33%) with informed consent and based on their age, divided them into 3 age groups, where each group was given a tag such as – G_1, G_2, or G_3, 10 participants per group. The demographic details of the 3 age groups are given in Table 5.

B. STUDY DESIGN

After recruitment, each participant was instructed about the 4 tasks that they had to perform. In each of these tasks, they had to go through an interface having *graphical* and *textual* contents. Each participant was given a unique pair of randomly chosen contents per task (*Step 1,* Fig. 8). Each participant was given 6 minutes for each task, during which eye gaze coordinates were recorded, analyzed, and the corresponding feature vector was generated (*Step 2,* Fig. 8). This feature vector was then passed on to the trained *SVM* classifier (*Step 3,* Fig. 8), which determined their visual intention ("TEXT" or "IMAGE") during each task (*Step 4,* Fig. 8). Since, during the experiment, coordinates of the detected pupils were recorded and the corresponding features were extracted, to remove bias in these coordinates, each of these contents was displayed at unique locations on the screen in such a way that they did not overlap. Once the intention was classified, it was tagged with the group tag of the participant (*Step 5*, Fig. 8). The workflow diagram of visual intention detection by age is outlined in Fig. 8. After the visual intentions of all the 30 participants (belonging either to the age group G_1, G_2, or G_3) had been classified as "TEXT" or "IMAGE", for any age group, G_i, the *Relative Interest* (*RI*) in *textual* (RI_{Text}) or *graphical* (RI_{Image}) contents was measured following (4) and (5), respectively.

$$RI_{TEXT}\left(G_i\right) = \frac{Countof \text{ ``}TEXT\text{''} \ as \ inference}{Total \ number \ of \ contents \ for \ group \ G_i} \times 100\% \tag{4}$$

$$RI_{Image}\left(G_i\right) = \frac{Count \ of \text{ ``}IMAGE\text{''} \ as \ inference}{Total \ number \ of \ contents \ for \ group \ G_i} \times 100\% \tag{5}$$

Finally, a semi-structured interview was conducted. For each participant, the experiment lasted for approximately 35 minutes (*4 tasks* $\times$ *6 minutes per task* + *10 minutes interview*). To cross-check the findings of our model, we analyzed the qualitative data, collected during the interview session, to find out their actual visual intention during each task. This analysis revealed that the model's detection was within the consensus of the user's interest.

C. RESULT ANALYSIS

Intuitively, visual intention is a subjective cognition process. However, it is of great interest how this behavior varies across users of different age groups. The findings of our experiment provided us with valuable insights into the variance of human visual intention with respect to their age. As seen from Fig. 9, for the young users (Group G_1, 16-20 years), the value for RI_{Image}, following (5), was found to be 77.50%, meaning that the users within this age group preferred *graphical* over *textual* contents in 77.50% of the cases. Similarly, for the middle-aged users (Group G_2, 21-30 years), the values for RI_{Text}, following (4), and RI_{Image}, following (5), were 42.50% and 57.50%, respectively, maintaining a neutral preference. However, for the elder users (Group G_3, 31-45 years), about 70% of them focused on *textual* content.

From the perspective of design principle, these user preferences, obtained by analyzing eye gaze data, may allow *UI/UX* designers to facilitate the cognitive process of the users of different age groups in HCI. For example, based on our experiment, if we want to design a gender-invariant interface for young users, the proportion of *graphical* contents will have to be higher than the *textual* ones so that maximum exchange of information can be achieved between the user and the interface. Again, to achieve similar goals for middle-aged users, the proportions of these contents will almost be the same due to minimal variation of their preference. However, for the elderly users, the proportion of *textual* contents will have to be greater than that of the *graphical* ones.

From the semi-structure interview, we found 29/30 participants were in the consensus with the classifier's detection of intention. Furthermore, we uncovered some applications from participants' responses on leveraging this technique for adaptive user interface design. One area where this can potentially add some interest is online news blogs. We found often participants feel uninterested on the materials due to not having data presented in infographics. However, we also found that the type of content is highly subjective to age. Therefore, having adaptive user interface is likely to increase users' engagement in this area. Based on the idea, if the type of content can be identified as the user's preference, this can also be leveraged for the personal recommendation of contents.

V. DISCUSSION

In this work, we have focused on the determination of visual intention to perceive textual or graphical information from interactive interfaces by analyzing eye gaze data in real-time using a low-cost regular webcam. We have tracked and recorded the coordinates of the eye pupils and defined

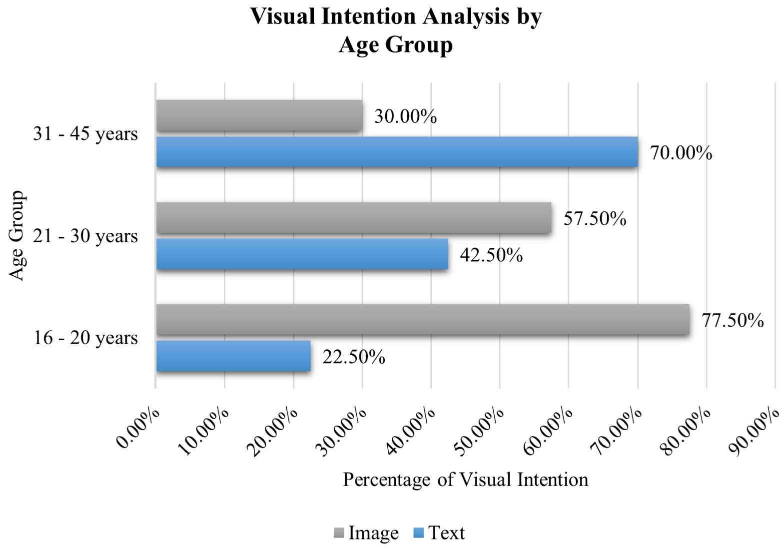


FIGURE 9. Analysis of visual intention (textual or graphical) among users of different age group.

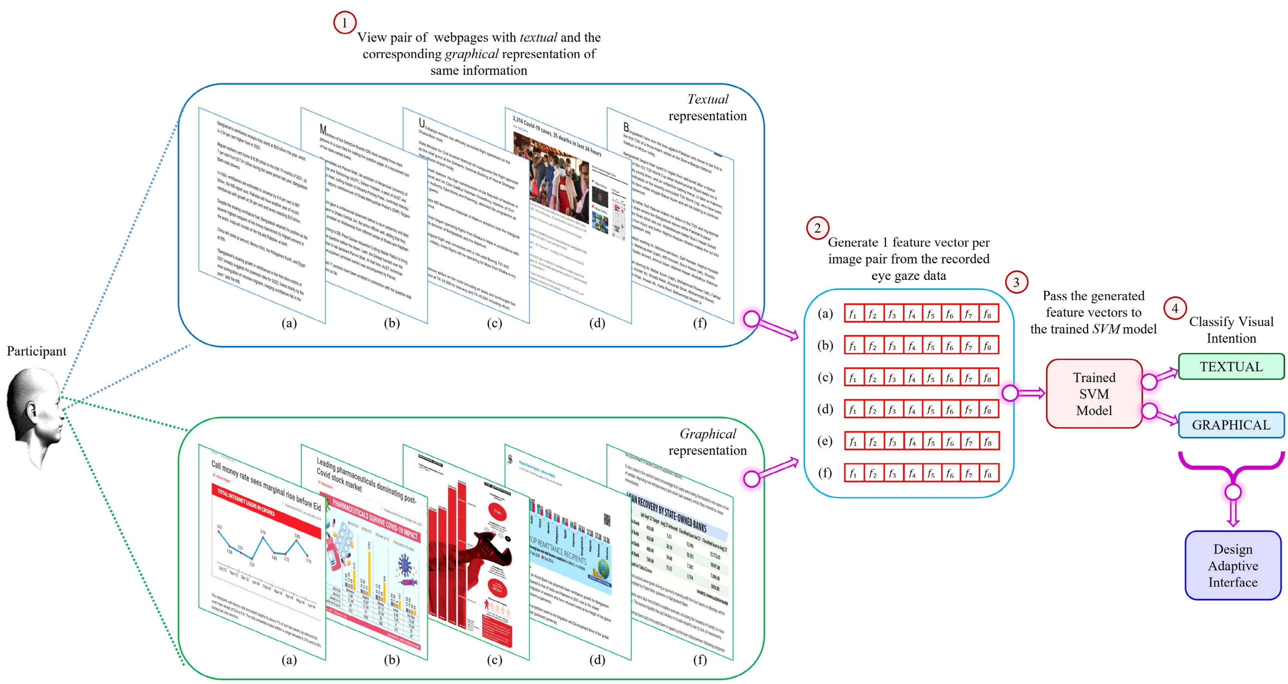


FIGURE 10. Workflow diagram of analyzing preference of textual or graphical representation of web page information through visual intention detection from eye gaze.

a feature vector containing 8 features that are sufficient for classifying visual intentions for retrieving textual or graphical contents. In this manner, we have analyzed the eye gaze data from 31 users and generated a dataset containing 124 samples, labeled as either TEXT or IMAGE. Using this dataset, we have performed a comparative analysis of 5 different classifiers such as KNN, GNB, RF, LR, and SVM. We have found SVM classifies this type of data reliably, having an *Accuracy* of 92.19% and an *Average Inferencing Time* of 1.47 ms (milliseconds). Among the eye gaze features, we have found that eye Movement Ratio (MR) and Average Fixation Count (AVG_FC) are vital for classifying visual intentions as textual and graphical. Furthermore, we have used our trained classifier (SVM) to conduct a user study where we have explored the variation in the relationship of visual intention of a user with respect to age and gender. From this user study, we have observed that the young users prefer graphical over textual contents more than the elder users, with the middle-aged users maintaining a neutral preference between the two contents.

The main motivation of this study was to explore whether a minimal number of eye gaze features can highlight certain user preferences for either textual or graphical contents that may help the UI/UX designers in the process of developing adaptive interactive interfaces, facilitating human cognition. Indeed, from our experimental results, using our proposed features, we have found that analyzing these data can play a vital role in this research area. In this study, we have tracked, recorded, and feature engineered *fixations*, *movement ratios* from eye gaze data using a low-cost regular webcam. We have analyzed the variation of the preference for *textual* or *graphical* contents across users of 3 different age groups and found the preference gradually shifted from *graphical* to *textual* contents with increasing age of the users, as seen from Fig. 9.

In recent times, analyzing user preferences while interacting with a web blog interface [50], [51] has become an emerging area of eye gaze research. The news portal presents similar news in infographics as well as texts. From visual information perspective, information can be presented in line, bar, pie, or tabular format. We can think of multiclass detection of visual intention with different types of information presented using graphs on such portals, e.g., when textual contents are overlaid on graphical contents. Subject to further investigation, such scenarios can be tackled by considering it as a different class (labeled as: "*Overlaid Class*") and train the model accordingly for generating inference on visual intention in such cases.

Extending to our idea, a potential research direction can be designing an adaptive news portal containing users' preferred infographics or texts based on personalized intention. Therefore, by detecting users' intention from their gaze, we may change the layout of the interface by adapting more graphical or textual contents based on their interest, resulting in an adaptive user interface design. The workflow diagram for such analysis, as shown in Fig. 10, can be considered. Another interesting investigation can be identifying users' engagement while visualizing certain data just by using their gaze information. If we can distinguish between graphs viewing patterns by training a classifier with users' gaze information, then we will be able to tell which type of graph is more engaging while giving a summary in a news portal just by analyzing users gaze information during inferencing.

Other potential applications of analyzing eye gaze information can be detecting attention during online classes by analyzing pupil movement patterns, uncovering students' plagiarism behavior from different screens during online proctoring, analyzing gender wise user preferences for certain types of interface color schemes and content types that reduces cognitive load and enhances immersion [52]–[54].

As mentioned earlier, for *textual* or *graphical* contents during training-testing, we have considered aspect ratios of 4:3 and 16:9. Future works should investigate the impact on gaze feature values (i.e., *MR*) having contents with different aspect ratios (e.g., 9:16 and 1:1). Also, the addition of new features such as *pupil diagonal movement variation*, *left to right*, and *right to left movement ratio* are likely to make this system generalizable beyond a fixed aspect ratio. Furthermore, another interesting feature that can be explored is the standard deviation (SD) of the feature AVG_FC.

Potentially, this type of tracker can be used in another avenue – the medical sector. Parkinson's patient encounters eye movement abnormalities. That includes hypometric and slow vertical saccades, normal horizontal saccades, saccadic pursuit. So, if we have a tracker trained on eye features of *Parkinson's patient* vs *Normal person*, then diagnosis of the disease may become easier for the doctor. A similar system can be leveraged for detecting other conditions such as *autism phenotype* [55], *multimodal depression* [56], *medical oculography* [57], *Alzheimer's disease* [58], and *Amyotrophic Lateral Sclerosis* (ALS) [59].

As a concluding remark, our study serves as a proof of concept for certain eye gaze features that can contribute to the design and development of interactive interfaces through the determination of visual intention of users of different age, facilitating their cognitive process while interacting with such interfaces. Subject to further investigation, enhanced user experience through intention aware interactive interfaces, facilitating disease detection can be accomplished through visual intention detection from eye gaze information.

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SHAHED ANZARUS SABAB received the B.Sc. (Eng.) degree in computer science engineering from the Islamic University of Technology (IUT), Boardbazar, Gazipur, Bangladesh, in 2015, and the M.Sc. degree in computer science from the University of Manitoba, Winnipeg, Canada, in 2020.

He is currently working in the domain of computer vision and natural language processing, as a Data Scientist. His specialization involves gesture-based interaction design, user study, machine learning, and visualization. In addition, he contributed to researches involving assistive technologies and disease prognosis.

Mr. Sabab and his team received the Champions Title (Project Showcasing) at the National ICT Fest, in 2014, and the Champions title at the Microsoft Imagine Cup from Bangladesh, in 2015, for a system designed for amputees.

MOHAMMAD RIDWAN KABIR received the B.Sc. (Eng.) and M.Sc. (Eng.) degrees in computer science and engineering from the Islamic University of Technology (IUT), Boardbazar, Gazipur, Bangladesh, in 2017 and 2022, respectively.

Since 2018, he has been working as a Lecturer with the Department of Computer Science Engineering, IUT. Earlier, he worked as a Lecturer with the Department of Computer Science Engineering, BRAC University, Dhaka, Bangladesh. His research interests include human-computer interaction, computer vision, assistive technology, machine learning, data analysis and visualization, embedded system development, and wearable devices.

Mr. Kabir has received the Runners Up Title (Project Showcasing) at the National ICT Fest, in 2016, the Champions Title (Project Showcasing) at Esonance, in 2017, the Top Five Innovative Projects Awards at BASIS Soft Expo, in 2020, and the BASIS National ICT Awards, in 2021. He has also become the Champions in Research and Development Category in the APICTA Awards (2020–2021).

SAYED RIZBAN HUSSAIN received the B.Sc. (Eng.) degree in computer science engineering from the Islamic University of Technology (IUT), Boardbazar, Gazipur, Bangladesh, in 2015, and the M.Sc. degree in applied statistics and data science from Jahangirnagar University, Savar, Dhaka, Bangladesh, in 2021.

He has over six years of experience with firmware development. His research interests include IoT devices, data mining-visualization, human computer interaction, computer vision, machine learning, and AI. His key strengths include designing system architectures, problem solving, and critical thinking capability.

Mr. Hussain and his team received the Champions Title (Project Showcasing) at the National ICT Fest, in 2014, the Champions Title at the Microsoft Imagine Cup from Bangladesh, in 2015, for a system designed for amputees, and the Runners Up Title at the National Hackathon, in 2016.

HASAN MAHMUD received the B.Sc. degree in computer information and technology from the Islamic University of Technology (IUT), Boardbazar, Gazipur, Bangladesh, in 2003, the M.Sc. degree in computer science from the University of Trento (UniTN), Italy, in 2009, and the Ph.D. degree in computer science from IUT, in 2021.

He is currently working as an Assistant Professor with the Department of Computer Science Engineering, IUT. He has been involved in HCI research, since 2009. He specializes in gesture-based interaction through machine learning approaches, affective computing, and assistive technology for the physically impaired.

HUSNE ARA RUBAIYEAT received the B.Sc. degree in computer science engineering from the Rajshahi University of Engineering and Technology (RUET), Rajshahi, Bangladesh, in 2004, the master's degree in biomedical engineering from Kyung Hee University, South Korea, in 2010, and the master's (Diploma) degree in technical education from the Islamic University of Technology (IUT), Boardbazar, Gazipur, Bangladesh, in 2012.

Currently, she is working as an Assistant Professor in computer science with the Natural Science Group, National University, Bangladesh, Boardbazar. Her research interests include sensor-based human activity recognition and HCI.

MD. KAMRUL HASAN received the Ph.D. degree from Kyung Hee University, South Korea, in 2010.

Currently, he is working as a Professor with the Department of Computer Science Engineering, Islamic University of Technology (IUT), Boardbazar, Gazipur, Bangladesh, where he is also the Founding Director of the Systems and Software Laboratory (SSL). His research interests include intelligent systems, software engineering, social network analysis, and data mining.