Reading the Minds Eye: Detecting Trauma-Vulnerability in Individuals by Analyzing Attention Through Eye-Tracking

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Abstract. In this work, we propose a novel approach for detecting and predicting trauma vulnerability in individuals by monitoring their attention to threat images using eye-tracking. We utilized a combination of statistical analysis, machine learning models and cognitive psychological theories. To do so, initially, an online survey was conducted with 183 participants to gather information about individuals' previous experiences with trauma. Based on the survey results, an image set was prepared, consisting of four categories: positive, neutral, general threat and trauma-relevant threat. 39 volunteers, categorized into trauma-exposed and non-trauma-exposed groups based on clinical diagnosis and previous treatment, then participated in an eye-tracking experiment, where they were presented with 10 slides containing 4 images from each category; each slide lasting for 6 s. Eye gaze patterns were recorded and processed during this period, which was used to extract different features that were later used for the machine learning models to train on. Our findings revealed that trauma-exposed group showed more attentional bias towards the specific trauma-relevant threat images than the non-trauma-exposed group. Results from training the models suggest that it is highly likely that predicting trauma vulnerability in individuals is possible and this demands further research.

Keywords: Trauma Detection · Eye Tracking · Machine Learning · Survey

1 Introduction

The importance of mental health cannot be overstated, as it has a direct impact on our overall well-being and the quality of our lives. It shapes our thoughts, emotions, and behaviors, playing a crucial role in how we handle stress, establish relationships, and navigate decisions. When mental health is neglected or compromised, it can lead to a range of challenges, including emotional instability, impaired cognitive function, strained relationships, and decreased productivity. Therefore, prioritizing mental health is essential for maintaining a

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balanced and fulfilling life. Trauma, within the sphere of mental health, refers to distressing events or circumstances that profoundly disrupt an individual's emotional and psychological equilibrium. The study of trauma highlights the critical link between mental health and traumatic experiences. Trauma can have long-lasting effects on an individual's psychological well-being, often resulting in conditions such as PTSD, anxiety, and depression [13]. The psychological impact of trauma varies from person to person, and not everyone who experiences trauma will develop a diagnosable mental health disorder [4,15]. Asides mental health impacts, trauma can contribute to a range of physical symptoms, such as sleep disturbances, chronic pain, headaches, gastrointestinal issues, and compromised immune function [9]. These physical manifestations can further exacerbate the emotional and psychological distress associated with trauma. One study even found out that an enduring effect of trauma exposure can be passed to offspring transgenerationally, which affects the expression of genes [18].

A comprehensive study was conducted across 24 countries worldwide, encompassing a diverse group of 68,894 adults from six continents. The aim was to evaluate the exposure of individuals to various types of traumatic events, with a total of 29 categories considered. The findings indicated that more than 70% of respondents reported experiencing at least one traumatic event; 30.5% were exposed to four or more [1]. Additionally, a separate survey involving 10,641 adults in Australia revealed that 57% of the population had encountered a traumatic event at some point in their lives. Notably, the study unveiled that men had a higher likelihood of experiencing most types of trauma, including multiple traumas, except in cases of sexual assault. Furthermore, the research highlighted that factors such as being female, younger in age, having limited educational background and residing in economically disadvantaged areas were associated with an increased probability of developing post-traumatic stress disorder (PTSD) after experiencing trauma. However, when considering a combination of factors, the specific nature of the trauma itself, particularly instances like sexual assault, emerged as a more influential predictor of PTSD development [10].

When it comes to trauma, individuals react and respond in unique ways, demonstrating a range of vulnerabilities and resilience. The concept of trauma vulnerability acknowledges that not everyone responds to traumatic events in the same manner [2]. Understanding why some people are more susceptible to the negative effects of trauma while others exhibit greater resilience requires consideration of various factors. It is important to emphasize that trauma vulnerability does not imply weakness or deficiency. It is a recognition that individuals have different strengths, resources, and capacities to cope with and recover from traumatic events. Understanding trauma vulnerability can inform the development of targeted interventions and support systems that help mitigate the negative effects of trauma and promote healing and resilience. The motivation of this study was to design a state of the art method that would be able to identify trauma-vulnerability in individuals, which would help in early intervention and prevention of traumatization, building resilience and coping skills and preventing long-term societal costs.

Numerous studies have demonstrated the connection between trauma and visual content. One of the recent studies showed that, a perceptual processing bias for trauma related stimuli may contribute to the involuntary triggering of intrusive trauma memories in PTSD [7]. In this context, understanding trauma vulnerability becomes crucial as it not only contributes to our comprehension of how individuals respond to digital stimuli but also informs the development of targeted interventions and support systems. Trauma, often exacerbated or triggered by digital content, can have far-reaching psychological implications, making it imperative to delve into its dynamics to ensure a healthier digital experience for all.

1.1 Motivation

In the context of Bangladesh, a developing nation with very limited awareness of mental health issues, a substantial number of trauma cases remain undiagnosed. Consequently, mental health disorders persist unchecked, often manifesting as conditions such as anger and depression. Even when overt signs of trauma exposure become apparent, individuals often hesitate to seek treatment due to the financial constraints associated with therapy and medication. Furthermore, discussing mental health remains a social taboo in some communities, making it challenging to access professional help. Against this backdrop, the primary driving force for this research endeavor is to investigate the feasibility of preemptively identifying individuals susceptible to specific types of trauma, with the aim of enabling early intervention to prevent the development of Post-Traumatic Stress Disorder (PTSD). Moreover, the methodology employed for this purpose is designed to be cost-effective, ensuring accessibility for a broad spectrum of the population, particularly in the resource-constrained context of a developing country like Bangladesh.

This study explores the following research questions in the context of Bangladesh.

- **RQ1:** Is it feasible to ascertain whether an unassuming individual, without a prior diagnosis, is predisposed to a specific form of trauma?
- **RQ2:** Is it possible to use visual attention to do this task?
- **RQ3:** What level of accuracy can be attained using a cost-efficient approach for accomplishing this?

This study aims to answer these queries by leveraging the innate human inclination to unconsciously direct attention towards visual stimuli. By combining data from both our survey and experimental phase, we train machine learning models to forecast an individual's vulnerability to trauma.

1.2 Attentional Bias

Visual attention is a cognitive process that allows individuals to selectively focus their visual perception on specific aspects of the environment while ignoring irrelevant or less salient information. It involves a combination of bottom-up processing, where attention is automatically captured by salient or novel stimuli,

and top-down processing, where attention is guided by internal goals, expectations, and prior knowledge. When presented with different visual stimuli, such as a series of images, individuals may demonstrate distinct attentional patterns. Each person's attentional biases are influenced by a range of factors, including their unique cognitive makeup, personality traits, interests, and emotional states. These biases result in variations in the allocation of attention and the duration of gaze toward specific visual elements [16]. Psychologically, attentional patterns can provide insightful information about an individual's cognitive and emotional processes. By analyzing these biases, we can gain a deeper understanding of cognitive mechanisms such as selective attention, perception, and memory. A lot of research has established that attentional bias is linked to an individual's threat processing [19]. The objective of the current study is to leverage this fact to try to detect trauma vulnerabilities in individuals.

2 Related Works

Numerous researches in the past have suggested attentional bias in people diagnosed with PTSD. In a study conducted by Wshah, Skalka, Price, et al. in 2019 [17], the researchers aimed to develop computational methods to effectively identify at-risk patients and provide better early interventions. The study demonstrated that an ensemble model, comprising a combination of support vector machines, naive Bayes, logistic regression, and random forest algorithms, accurately predicted elevated PTSD symptoms with an area under the curve (AUC) of 0.85. Remarkably, only seven self-reported items or features were necessary to achieve this AUC. The self-reported features were collected through surveys administered via smartphones.

In another study conducted by Kimble et al. [5], they explored the differences in attentional patterns between depression and post-traumatic stress based on relevant literature. The researchers tracked the participants' eye movements while they viewed a series of 30 neutral but ambiguous and complex pictures on a computer sceen. Their findings revealed that hypervigilance scores and negative views of the world were predictors of both the number of fixations and the are of the picture covered by the participants' gaze. Based on their findings, the researchers concluded that there are distinct gaze patterns associated with pos-ttraumatic stress but not depression following trauma.

Eye tracking technology was utilized by Kimble et al. [6] to examine visual orientation and attention patterns in 19 veterans of the Iraq war. The objective was to investigate their responses to traumatic and neutral stimuli. The results indicated that veterans who reported higher levels of PTSD symptoms exhibited larger pupil sizes in response to all negatively valenced pictures compared to veterans with lower PTSD symptoms. Additionally, those with higher PTSD symptoms spent more time fixating on the negatively valenced stimuli.

A more detailed study was conducted by Thomas et al. [12] in 2013. 55 individuals were divided into three groups: clinical PTSD diagnosed, subthreshold

symptoms of PTSD, and a group with no trauma exposure. The researchers aimed to investigate the attentional patterns of these groups by tracking and recording their eye gaze while viewing sets of four images presented for 6 s. The images were categorized into positive, neutral, negative, and either general threat or trauma-relevant threat images. The results revealed that both the clinical PTSD and subthreshold symptom groups exhibited a higher attentional bias towards trauma-relevant threat images compared to the group with no trauma exposure. However, no significant group differences were observed for general threat images. Additionally, a time course analysis of the attentional patterns was conducted. The analysis demonstrated that participants with clinical symptoms of PTSD displayed evidence of avoidance towards threat images. This finding suggests that individuals with clinical symptoms of PTSD tend to actively avoid engaging with trauma-relevant threat stimuli.

3 Methodology

Our study involved several sequential steps that aimed to explore the effects of traumatic experiences on individuals. The initial phase encompassed an online survey, which included a comprehensive questionnaire that was designed to gather a wide range of information from the participants. This questionnaire sought to gather general participant information while also delving into specific details concerning their past traumatic experiences. Subsequently, leveraging the gathered information on traumas, our focus shifted towards the creation of an image set specifically tailored to the study's objectives, which would serve as the stimulus to the experiment. With the image set prepared, we progressed to the main experiment, wherein we tracked and recorded participants' eye-gaze patterns while they viewed a slideshow of images. This system allowed us to record and analyze participants' gaze fixation points, saccades (rapid eye movements between fixations), and overall eye-gaze patterns during the image presentation. By analyzing the recorded eye-gaze patterns, we aimed to uncover patterns of visual exploration, including areas of heightened attention and potential avoidance behaviors, related to the traumatic experiences reported in the initial online survey. Lastly, we used the data collected to train and evaluate various predictive models to assess the effectiveness of these models in predicting whether an undiagnosed individual is vulnerable to a certain type of trauma (Fig. 1).

3.1 Online Survey

To gather relevant data, we developed a comprehensive online questionnaire. The questionnaire aimed to capture general information about individuals, such as their age, occupation, and living conditions. Additionally, we included specific inquiries regarding their past traumatic experiences such as domestic violence, road accident, animal attack, abortion/miscarriage, emotional abuse, robbery, childhood bullying, physical abuse, sudden unexpected death of loved one, sexual assault, suicide attempt, divorce etc. We also inquired about their engagement

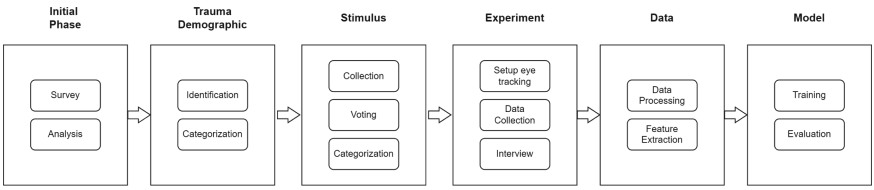


Fig. 1. Flow chart of methodology

in therapy or counseling to distinguish participants with a history of trauma exposure. Approximately 180 individuals participated in the survey (Figs. 2 and 3).

3.2 Stimuli

The stimulus set consisted of 40 images carefully selected from a larger collection. The selection process was guided by the results obtained from the initial survey. The images were categorized into four distinct categories: positive, neutral, general threat, and trauma-relevant threat. To determine the category assignment of each image, a smaller study was conducted in which individuals rated the images. The rankings provided valuable insights into how the images were perceived and were then appropriately categorized (Fig. 4).

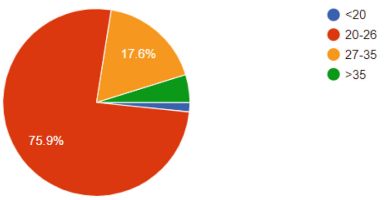
3.3 Participants

The study consisted of 39 individuals, comprising 21 males and 18 females. To facilitate the analysis, we divided the participants into two distinct groups:

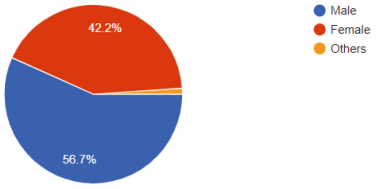
- **Trauma Exposed Group:** This group consisted of 18 participants who had experienced various forms of trauma. Among the, 5 individuals had been clinically diagnosed with trauma-related conditions and had received medication for their past traumas. Additionally, 13 participants had undergone some form of behavioral therapy at some point of their lives to address their trauma experiences.
- **Non-Trauma Exposed Group:** The remaining 21 participants had no significant history of trauma. These participants reported that they had not experienced any major traumatic incidents nor had they received any diagnoses related to trauma

3.4 Apparatus

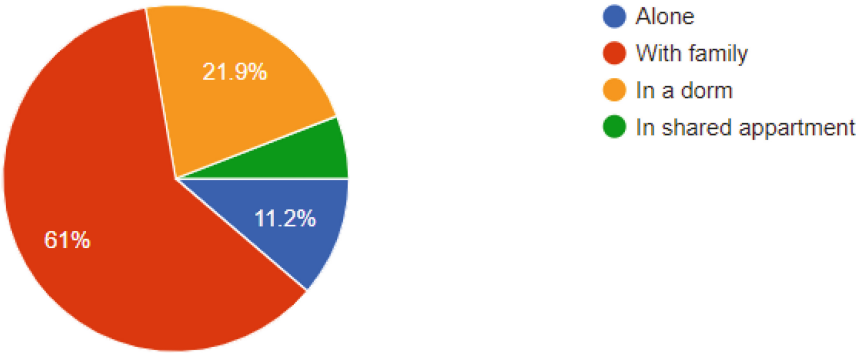
WebGazer [8], an online eye tracker that leverages the built-in webcams commonly found in laptops and mobile devices was used to track and record the participants' eye movements. It incorporates a self-calibration mechanism by observing how web visitors interact with the web page and trains a mapping between eye features and screen positions.



(a) Age Distribution



(b) Gender Distribution



(c) Living Condition

Fig. 2. Results from the survey

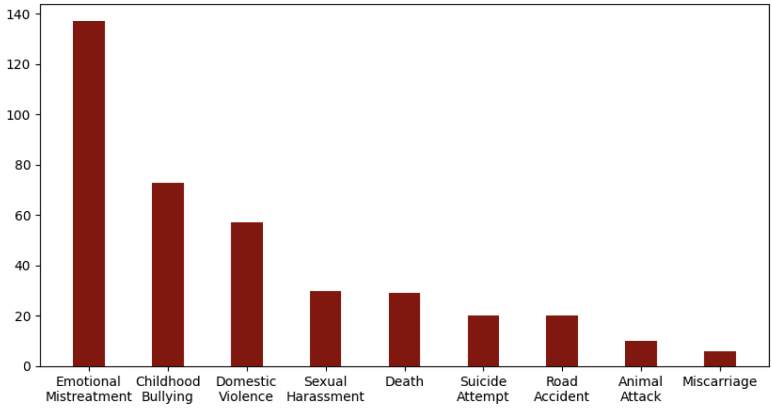


Fig. 3. Major Traumas in people

3.5 Experiment

Questionnaire. Prior to commencing the experiment, each participant was engaged in a preliminary questionnaire session. The purpose of this session was

(a) General Threat (b) Trauma Relevant

(c) Positive Image (d) Negative Image

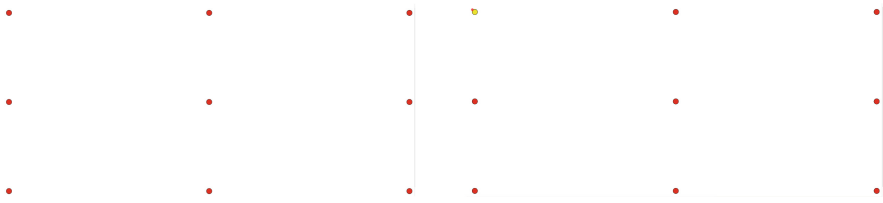
Fig. 4. Example of different categories of images

to gain insights into the participant's specific trauma history, the measures they had taken to address it, and how it had affected their life. This initial interaction aimed to establish a better understanding of each participant's unique experiences and provide context for the subsequent experiment.

Environment. Participants were positioned in front of a display screen with a with their faces directed towards a webcam mounted on the screen. The display screen's back faced a wall to ensure that there was no visual distractions behind the screen. Participants who wore corrective glasses were kindly requested to remove them for the duration of the experiment. This step was taken to enhance the precision of eye tracking measurements.

Calibration. The first phase of the experiment was a calibration process to establish accurate mapping between participants' eye positions and specific locations on the screen. A white screen displaying nine dots arranged across the screen was presented to the participants. They were then instructed to fixate their gaze on one of the red dots and proceed to register five mouse clicks on that particular dot. It was emphasized that they should refrain from blinking during the registration of clicks. Each click made by the participant was utilized to establish a precise mapping between their current eye position and the cor-

responding location of the dot on the screen. Once five clicks were successfully recorded, calibration for that specific point was accomplished. The same process was then repeated for the remaining eight dots on the screen (Fig. 5).



(a) 9 red dots on the screen (b) Top-left point is calibrated

Fig. 5. Calibration

Accuracy. To evaluate the accuracy of the calibration, additional mappings between participants' eye positions and specific regions on the screen were performed. The screen was divided into four distinct areas: top left, top right, bottom left and bottom right. Each of these regions was colored red for a duration of 3 s and the participants were requested to fixate their screen on that particular region. If the predicted participants gaze also fell on that region, the predicted gaze was considered accurate. The total time period where the predicted gaze was accurate was calculated to measure the accuracy of eye tracking. An average accuracy of 88%, with a peak accuracy of 95% was achieved during calibration. This validates the reliability of the eye tracking mechanism.

Procedure. The core component of the experiment involved presenting participants with a slideshow comprising four images per screen. A total of 10 slides were shown, resulting in a presentation of 40 images overall. Each screen consisted of four distinct categories of images: positive, general threat, trauma-relevant threat and neutral images. Each screen was displayed for a duration of 6 s, which is a little short of the human attention span [11].

3.6 Data Collection

For each of the four categories of images displayed, two key pieces of information was collected:

- **Looked At Times:** The timestamps when the gaze point entered the image
- **Looked Away Times:** The timestamps when the gaze point moved away from the image

Based on these two timestamps, various parameters were measured that would later be used for the training purposes of the models. Each set of images yielded seven specific features; with four categories of images, a total of 28 features were extracted. The seven features for each set of images are:

- *Total Fixation Duration:* Cumulative duration during which participants' gaze remains fixated on the particular image
- *Total Fixation Count:* The number of times participants' gaze fixates on that specific image. It represents the frequency of attentional shifts towards the image.
- *Average Fixation Duration:* Mean duration of individual fixations on that particular image. A longer average fixation duration suggests that participants are more engaged or immersed in the content of the image, whereas a shorted duration may indicate a more rapid scanning or less focused attention.
- *Average Gap Duration Between each Fixation:* The temporal intervals or pauses that occur during participants' gaze transitions within the image. A shorter average gap suggests that participants quickly move their gaze from one fixation to the next without much interruption which further suggests that participants look at the specific image more quickly which could be a result of potential bias towards that image.
- *Attention Over Time:* The 6-second time window was divided into three equal time windows of 2 seconds each:
  - Initial (0–2 seconds): This captures the initial fixation point of each participant, providing insights into the image that initially draws their attention
  - Middle (2–4 seconds): This captures the shifting of participants' eye gaze between different images after the initial attraction.
  - Final (4–6 seconds): This captures the last point of attention for each participant.

4 Results

The variables were the seven features for each category of images. Firstly, the data was divided into two groups, each corresponding to either the trauma exposed group or the non-trauma exposed group. The variables were calculated by taking an average of all the participants' data in each group. Then, the variables were summed over all the four types of category of images to make a comparison between them.

4.1 Percentage of Total Fixation Duration of Each Image Type

Table 1 presents the total fixation duration of two distinct groups of individuals towards the four image categories. The attention distribution of the trauma exposed group to these categories is displayed in the third column. The trauma exposed group allocated approximately 31.2% of their fixation time

to trauma relevant threat images, which is the highest proportion among the categories. Conversely, the non-trauma exposed individuals exhibited a lower attentional focus on trauma relevant threat images, with only 24.4% of their fixation time directed towards this category This pattern of attentional bias is consistent with the findings of existing literature on the topic [12]. Furthermore, the most attended category for the non-trauma exposed group is the positive images, accounting for 28.6% of their total fixation time. Interestingly, the trauma exposed individuals also displayed considerable attention towards positive images, with 27.5% of their fixation time directed to this category, making it the second most attended category for them. This suggests a bias towards positive images in both groups of people. However, for the non-trauma exposed individuals, the difference in total fixations between positive and general threat images is minimal, only 1.1%. This indicates that their attention is evenly divided between general threat and positive images. On the other hand, the trauma exposed individuals exhibit a greater disparity in fixation times between these categories. This finding suggests that non-trauma exposed individuals display a bias toward negative images [14]. In both cases, participants showed the least amount of fixation time on neutral images.

Table 1. Percentage of Total Fixation Duration

Image Category	Trauma Exposed	Non-trauma Exposed
Positive	27.5%	28.6%
Neutral	16.7%	19.5%
General Threat	24.6%	27.5%
Trauma Relevant Threat	31.2%	24.4%

4.2 Percentage of Average Fixation Duration

In Table 2, when ranking the images based on the average fixation duration of the trauma-exposed group, we observed that trauma-relevant threat images had the highest average duration (30.9%), followed by general threat images (26.1%), positive images (23.5%), and neutral images (19.5%). This ranking contradicts the ranking based on total fixation duration, where positive images ranked second and general threat images ranked third. However, the attentional pattern of the non-trauma-exposed group remained consistent when comparing average fixation duration and total fixation duration. The non-trauma-exposed group exhibited an attentional pattern in a non-increasing sequence, with general threat images receiving the highest average fixation duration (27.9%), followed by positive images (26.4%), trauma-relevant threat images (25.6%), and neutral images (20.1%).

Table 2. Percentage of Average Fixation Duration

Image Category	Trauma Exposed	Non-trauma Exposed
Positive	23.5%	26.4%
Neutral	19.5%	20.1%
General Threat	26.1%	27.9%
Trauma Relevant Threat	30.9%	25.6%

4.3 Percentage of Total Fixation Count

The total fixation count refers to the cumulative number of times participants fixated on a specific category of image throughout the duration of the experiment. Table 3 displays the percentage of the average fixation count per screen. The trauma exposed group had a 33.3% fixation count for positive images and 16.7% for general threat images. This suggests that the trauma exposed group tended to revisit positive images more frequently. This helps explain why the average fixation duration for general threat images was higher compared to the average fixation duration for positive images in this group. In the case of the trauma exposed group, the average fixation count for positive images is higher than that for general threat images. As a result, the average fixation duration for positive images is shorter compared to the average fixation duration for general threat images in this group. This could suggest that although the trauma exposed group spent more overall time looking at positive images, *they had a harder time diverting their attention away from general threat images each time they fixated on them.*

Table 3. Percentage of Total Fixation Count in a screen

Image Category	Trauma Exposed	Non-trauma Exposed
Positive	33.3%	16.7%
Neutral	16.7%	33.3%
General Threat	16.7%	16.7%
Trauma Relevant Threat	33.3%	33.3%

5 Analysis

Table 4 shows the proportion of the fixations on smaller time windows of 2 s over the 6 s duration of a slideshow presentation in our experiment.

For the trauma exposed group of individuals; during the first 2 s, there was a significant bias towards general threat images (35.8%), whereas the percentage of attention towards trauma relevant threat images was only 26.3%, even

Table 4. Attention Over Time Span

Image Category	Trauma Exposed			Non-trauma Exposed		
	0–2 s	2–4 s	4–6 s	0–2 s	2–4 s	4–6 s
Positive	27.6%	26.2%	25.3%	26.6%	26.8%	28.4%
Neutral	10.3%	20.1%	14.1%	12.3%	19.4%	15.5%
General Threat	35.8%	29.3%	28.2%	36.4%	28.5%	30.9%
Trauma-relevant threat	26.3%	24.4%	32.4%	24.7%	25.3%	25.2%

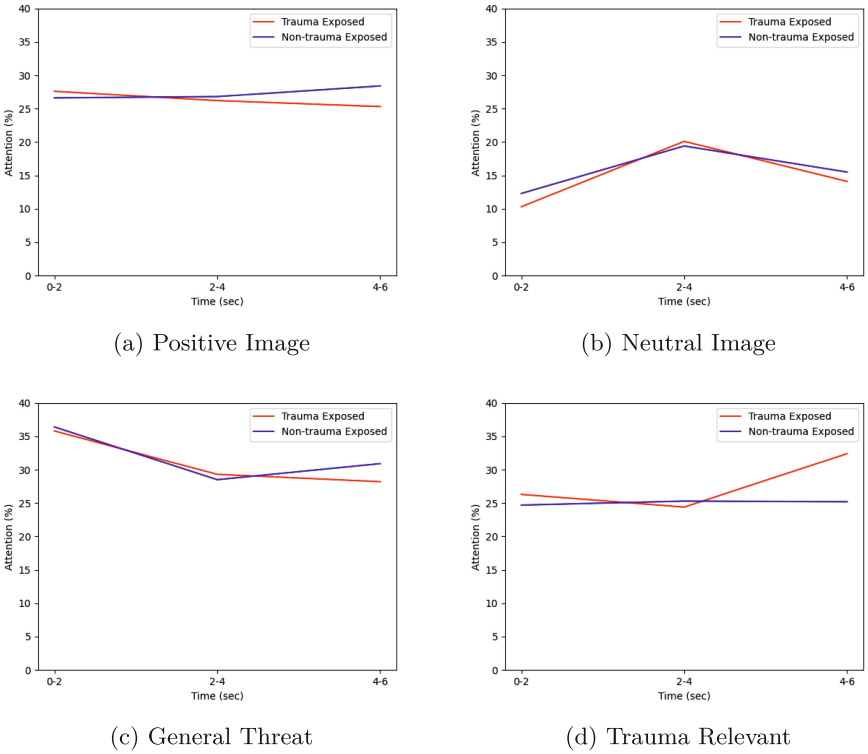
lower than that of positive images (27.6%). In the subsequent 2-second time window, the attention towards all categories decreased, but the attention towards neutral images increased significantly (20.1%). In the final time window of 2 s, the attention towards trauma relevant threat images increased significantly to 32.4%. Notably, the rankings of the categories at this time window align with the rankings of average fixation duration. This pattern might indicate that trauma exposed individuals initially showed avoidance towards trauma relevant threat images and exhibited a stronger fixation on general threat images. However, as time progressed, they looked over all the images on the screen, as reflected by the sudden rise in attention towards neutral images during the middle time window. Eventually, they directed most of their attention towards trauma relevant threat images in the final time window (Fig. 6).

One notable observation is that these individuals generally did not show any significant change in their attentional pattern across the different time windows for any of the categories. For instance, their attention towards positive images remained relatively consistent throughout the three time periods, with values of 26.6%, 26.8%, and 28.4%, which are all close to each other. Similar consistency can be observed for most other image categories, except for neutral and general threat images. The attention towards neutral images increased during the middle time window of 2–4 seconds, rising from 12.3% to 19.4%. The attention towards general threat images decreased during this middle time window, declining from 36.4% to 28.5%.

By comparing the data from the trauma exposed and non-trauma exposed groups side by side, it can be inferred that general threat images were the first to capture attention in both groups. This observation aligns with the general notion of a negativity bias, which suggests that individuals tend to pay more attention to negative or threatening stimuli [14].

6 Models Training and Evaluation

The data were labeled into a positive class (trauma exposed) and negative class(non-trauma exposed). The aim was to train supervised learning models on these labeled datasets to develop a predictive model. This model would be able to take an unlabeled data point from an individual who has not been exposed



(a) Positive Image (b) Neutral Image

(c) General Threat (d) Trauma Relevant

Fig. 6. Attention distribution over time span

to trauma and determine whether their gaze patterns align more closely with the positive class (trauma exposed) or the negative class (non-trauma exposed). If the individual's gaze pattern exhibited similarities to the positive class, we could infer that they potentially possess vulnerability to trauma. This detection of trauma vulnerability constituted the primary focus of our research (Fig. 7).

6.1 Training and Validation

Due to the dataset being small, k-fold cross validation was used to mitigate overfitting of data [3]. The dataset was initially shuffled randomly and divided into k equal partitions. For each partition, it was held out as the validation data while the model was trained on the remaining $k-1$ partitions. The model's performance was then evaluated by measuring the error using the held-out data as validation. This process was repeated for each partition, ensuring that every partition was used as the validation data.

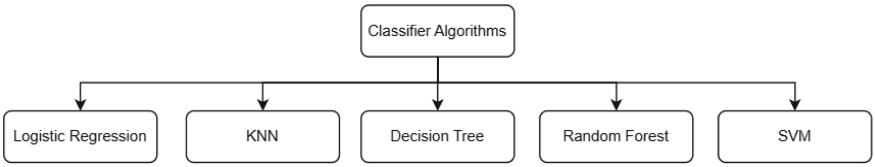


Fig. 7. Classification algorithms used

Table 5. Performance Metrics of the models

Classifier	Accuracy	Precision	Recall
Logistic Regression	.60	.53	.55
KNN	.79	.75	.72
Decision Tree	.68	.65	.60
Random Forest	.80	.77	.78
SVM	.68	.62	.58

6.2 Evaluation

Table 5 presents a summary of the performance metrics for the different models used. As anticipated, logistic regression performed poorly, likely due to its suitability for linear datasets with simpler structures. Since the dataset had a large number of features, logistic regression struggled to yield satisfactory results. The most successful models based on the performance metrics were KNN and Random Forest. Although Random Forest outperformed KNN in all metrics, it was found that KNN performed equally well due to the dataset's inherent characteristics, where similar classes of data tend to cluster together. Even though the models actually overfit the data, the results are suggestive that a predictive model could be used to match the attentional bias of an unsuspecting individual with the profile of a trauma exposed individual; this in turn could potentially be used to *predict whether an individual is vulnerable to certain types of trauma.*

7 Limitations and Future Work

The main limitation of the present study was the scarcity of data. To get a better evaluation of the models, it is necessary that those be trained on a large scale of data, taken from a diverse group of individuals. The data collected in the study was predominantly homogeneous, primarily comprising individuals within the age group of 20–26. This limited diversity may impact the generalization of the findings and their applicability to a broader population. Another limitation was related to the eye tracking method employed in the study. While cost-efficient, the accuracy of the eye tracking measurements was not optimal. This compromised the precision of data analysis. To address this issue, future research could

explore the use of more precise eye tracking instruments or techniques to enhance the accuracy of gaze tracking measurements.

Moving forward, it is crucial to overcome these limitations and address the gaps in the present study. One significant aspect to consider for further development of this work is the collection of a larger dataset. While the current dataset has provided valuable insights, expanding the sample size would offer a broader perspective and enhance the generalizability of the findings. A larger dataset allows for a more comprehensive representation of the target population, capturing a wider range of experiences, backgrounds, and demographics. Collecting data from a diverse set of population also provides the opportunity to explore subgroup analyses, investigating potential variations in trauma vulnerabilities based on factors such as age, gender, socioeconomic status, living conditions and even on culture.

Exploring alternative methodologies and technologies for eye tracking could improve the accuracy and reliability of the gaze data collected. This could involve utilizing more advanced eye tracking equipment or integrating multiple modalities for a comprehensive assessment of attentional responses. Another interesting avenue of research would be to focus on the prediction of specific types of trauma-vulnerability, rather than the general classification of individuals as trauma vulnerable. By focusing on the prediction of specific traumas, researchers and practitioners would gain insights into the prevalence and patterns of different types of traumatic experiences within a population.

A fascinating avenue of research would involve investigating the effectiveness of behavioral therapy in overcoming trauma. By analyzing the eye gaze patterns of individuals before and after undergoing behavioral therapy, it can be investigated whether there are any observable changes in their attentional responses to trauma-related stimuli.

8 Conclusion

The study proposed the utilization of various models aimed at identifying individuals who are vulnerable to trauma, employing a cost-efficient approach that relies solely on a webcam. By leveraging the capabilities of a webcam, the approach in this study offers a practical and cost-effective solution for assessing trauma susceptibility in individuals. Moreover, the findings highlight the neglect of trauma effects and the overall ignorance towards mental health in Bangladesh. The taboo surrounding discussions about mental health has led to many trauma-vulnerable individuals remaining undiagnosed and untreated, living their lives with significant distress. This quantitative analysis underscores the urgent need for trauma care and increased mental health awareness in Bangladesh.

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