AI-Based Eye Tracking System for Real-Time Prediction of Customer Interest in Electric Vehicle Product Design

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ABSTRACT

Electric vehicle (EV) manufacturers continuously develop new design concepts to attract customers, understanding which design elements truly capture user attention remains difficult. Traditional feedback methods such as surveys and interviews often fail to reflect actual customer interest because they depend on subjective opinions rather than real viewing behaviour. To address this limitation, this paper presents an AI Based Eye Tracking System for Predicting Customer Interest in EV Product Design**. The proposed system uses a webcam-based eye-tracking approach to capture real-time gaze direction, blink rate, focus duration, and facial landmarks while multiple users observe EV design videos. In addition, facial expressions are analysed using a convolutional neural network trained on a public emotion recognition dataset to identify user emotions such as happy, neutral, sad, angry, and confused during viewing. The extracted attention and emotion features are processed using a Decision Tree classifier to estimate customer interest levels as interested, moderately interested, or less interested for different EV design regions. The system is implemented as a Flask-based web application that provides graphical visualizations such as charts and graphs to present gaze distribution, session statistics, and interest classification results. By combining visual attention and emotional response into measurable feedback, the proposed approach offers a practical and objective method for evaluating EV product designs and supporting data-driven design decisions in the automotive industry.**

Keywords: Eye tracking, Electric vehicle design, Customer interest prediction, Visual attention analysis, Machine learning, Gaze detection, Flask web application.

INTRODUCTION

The rapid growth of electric vehicles (EVs) has increased competition among manufacturers to create designs that attract customer attention and improve user experience. In the early stages of vehicle development, designers often rely on customer feedback to understand preferences related to vehicle shape, lighting, dashboard layout, and overall appearance. However, collecting reliable feedback during the design phase remains difficult because traditional methods such as surveys and interviews depend mainly on personal opinions and memory rather than actual visual behaviour. As a result, designers may not clearly identify which design elements truly capture customer interest.

Eye-tracking technology offers a more objective way to understand user attention by measuring where and how long a person looks at visual content. Human gaze behaviour directly reflects attention and interest, making eye-tracking useful in fields such as marketing, product design, and user experience analysis [18], [22]. Recent studies show that visual attention patterns can reveal customer preferences and decision processes more accurately than self-reported feedback [7], [20]. In automotive research, eye-tracking has been used to evaluate vehicle interfaces and interior design elements, helping designers understand how users interact with vehicle components [16], [21].

With the availability of webcams and computer vision methods, eye-tracking can now be implemented using standard cameras instead of expensive hardware devices. Webcam-based gaze tracking systems enable real-time attention monitoring in natural viewing conditions and allow scalable user studies [1], [10]. Machine learning techniques further improve the analysis of gaze data by identifying patterns related to user behaviour, interest, and attention levels [3], [4]. These advances make it possible to build practical systems that automatically estimate customer interest from visual behaviour.

Based on these developments, this paper proposes an **AI Based Eye Tracking System for Predicting Customer Interest in EV Product Design**. The system captures real-time gaze direction, blink behaviour, and focus duration while users observe EV design images and videos. These visual attention features are analysed using a machine learning model to estimate customer interest levels for different vehicle design regions. The proposed system is implemented as a Flask-based web application that supports multiple users and provides graphical visualization of attention patterns. By converting human visual behaviour into measurable feedback, the system offers designers an objective tool to evaluate EV product designs and identify design elements that attract or lose customer attention.

PROBLEM STATEMENT

EV manufacturers need better ways to understand which vehicle design features attract customer attention. Traditional methods such as surveys and interviews mostly depend on what people say, which may not match how they actually look at designs. Designers often cannot clearly know which parts of an EV users focus on or find interesting. There is a need for a system that can measure real user attention while people view EV designs. Hence, a real-time eye-tracking approach can help predict customer interest and support better EV design decisions.

OBJECTIVES OF STUDY

The objective of this study is to develop an AI Based Eye Tracking System for Predicting Customer Interest in EV Product Design that can understand how users look at EV designs. The system captures eye gaze, blinking, focus time, and facial emotions while users watch EV videos. Using this information, it predicts whether the user is interested, moderately interested, or less interested in the design. The aim is to help designers know which EV features attract more user attention.

LITERATURE REVIEW

Understanding customer attention through visual behaviour has become an important research area in recent years. Eye-tracking technology provides direct information about where users look and how long they focus on specific objects, which helps researchers study human interest and decision-making processes. Previous studies have shown that gaze patterns and fixation duration can reveal user preferences more accurately than traditional feedback methods such as questionnaires or interviews [20], [22]. Eye-tracking has therefore been widely applied in consumer behaviour analysis, marketing, and product evaluation to understand how visual attention influences choices [2], [18].

Several researchers have explored the use of eye-tracking for design evaluation and user experience analysis. Guo et al. demonstrated that eye-tracking data can support visual communication and design assessment by identifying which design elements attract attention [14]. Similarly, Šola et al. showed that visual attention patterns can be used to evaluate engagement with digital design content [12]. Studies in neuromarketing also confirm that eye movement behaviour reflects user interest and can guide product presentation strategies [18]. These findings indicate that eye-tracking can provide objective insights into user perception during product design.

In the automotive domain, eye-tracking has been applied to analyse driver interaction and vehicle interface usability. Li and Hao used gaze data to study how users visually search automotive human–machine interfaces, showing that eye-tracking helps identify important interface regions [16]. Song et al. applied eye-tracking in automotive interior design evaluation and demonstrated its usefulness in understanding consumer preferences in vehicle design [21]. These studies highlight the relevance of visual attention analysis for vehicle-related design research, which supports the use of eye-tracking in EV product design evaluation.

Recent advances in webcam-based eye-tracking have made gaze analysis more accessible and scalable. Saxena et al. showed that webcam eye-tracking models can achieve reliable gaze and blink detection without specialized hardware [1]. Yang and Krajbich further demonstrated that online webcam eye-tracking can capture user attention patterns in real-world viewing conditions [10]. These approaches enable multi-user and remote eye-tracking studies, which are suitable for design evaluation applications such as EV product testing.

Machine learning has also been integrated with eye-tracking to improve behaviour prediction and attention analysis. Rodrigues et al. combined eye-tracking with machine learning and facial analysis to understand consumer behaviour patterns [2]. Al-Omair reviewed how gaze-based features can enhance recommender systems by capturing real-time user preferences [3]. Ibragimov and Mello-Thoms showed that machine learning methods can effectively analyse gaze data to identify patterns related to perception and decision processes [4]. These studies confirm that combining eye-tracking with machine learning can provide automated and objective user interest estimation.

Other works have explored specialized applications of gaze-based systems such as communication interfaces, safety monitoring, and attention-driven interaction. Sun et al. proposed an improved eye-tracking detection method using deep learning models [7], while Madni et al. applied eye movement analysis for driver state recognition [5]. Although these studies focus on different domains, they demonstrate the capability of eye-tracking systems to capture meaningful behavioural information from eye movements.

Overall, research confirms that eye-tracking can objectively measure user attention, machine learning can interpret gaze behaviour, and webcam-based systems allow scalable deployment. However, limited work has focused specifically on predicting customer interest in electric vehicle product design using real-time gaze behaviour. Therefore, the present work proposes an **AI Based Eye Tracking System for Predicting Customer Interest in EV Product Design**, which combines webcam-based gaze tracking and machine learning analysis to estimate user interest levels for EV design elements.

PROPOSED SYSTEM ARCHITECTURE

This section explains how the proposed **AI Based Eye Tracking System for Predicting Customer Interest in EV Product Design** works. The system studies how users visually observe EV design videos and converts their viewing behaviour into measurable attention and emotion features. These features are then used to predict whether the user is interested, moderately interested, or less interested in the EV design. The complete workflow begins with capturing user viewing behaviour and ends with interest prediction and graphical result display inside a Flask-based web application.

The first stage of the system is the visual display module, where EV design images and videos are presented to users through a web interface. This ensures that all participants view the same design content under similar conditions. While users watch the EV designs, their face and eye movements are recorded in real time using a standard webcam. This webcam-based setup removes the need for specialized eye-tracking hardware and allows easy multi-user testing.

The captured video frames are processed in the face and eye detection stage. In this step, the system identifies the face region and locates the eyes using facial landmark detection. Important eye details such as gaze direction, blink events, and eye position are extracted from each frame. These measurements help determine where the user is looking and how long attention remains on specific parts of the EV design. In this way, raw webcam video is converted into meaningful visual attention information.

After detection, the extracted eye features are passed to the attention analysis stage. Here, the system calculates attention measures such as fixation duration, blink rate, gaze distribution, and focus time across different vehicle regions. The EV display is divided into areas such as front, side, and interior so that gaze points can be linked to specific design components. These calculated values represent how much visual attention each design element receives and are stored for further analysis.

In addition to gaze behaviour, the system also analyzes user emotion during viewing. Facial images obtained from webcam frames are processed using a convolutional neural network trained on a public Kaggle facial emotion recognition dataset. The model identifies emotional states such as happy, neutral, sad, angry, or confused. Emotion information complements gaze data because positive or focused expressions often indicate higher engagement, while confused or disengaged expressions may indicate reduced interest.

The combined attention and emotion features are then provided to the machine learning prediction stage. A Decision Tree classifier analyzes these behavioural patterns and predicts the level of customer interest. The system classifies each viewing session into three categories: interested, moderately interested, or less interested. The prediction is based on learned relationships between gaze behaviour, blink patterns, emotional response, and user attention distribution.

The final stage of the system is result visualization. The predicted interest level and attention statistics are presented as charts and graphs in the web dashboard. These visual outputs show gaze distribution, attention percentage across EV regions, and viewing duration. Designers can easily understand which vehicle parts attract more attention and which areas receive less focus. Graph-based visualization provides clear comparison of user interest without using heatmaps.

All processing stages are integrated within a Flask-based web application that manages user interaction, video capture, data processing, and result display. The system supports multiple users and operates in real time, making it suitable for EV design evaluation studies. By converting user visual behaviour and emotional response into measurable feedback, the proposed system provides a practical tool for predicting customer interest in EV product designs.

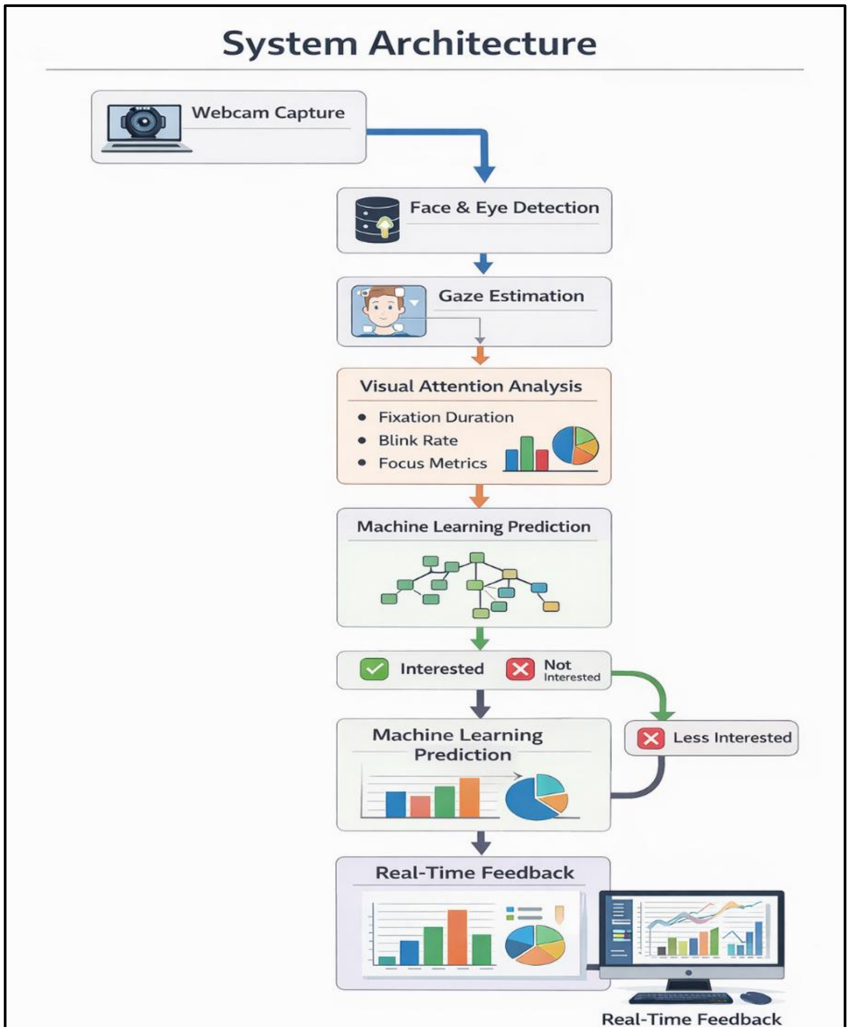

Fig 1. System Architecture

METHODOLOGY

This section explains how the proposed **AI Based Eye Tracking System for Predicting Customer Interest in EV Product Design** operates. The system observes how users look at EV design videos and converts their viewing behaviour and facial expressions into measurable attention and emotion information. These values are then used to predict whether the user is interested, moderately interested, or less interested in the EV design.

The complete process includes webcam video capture, face and eye analysis, gaze tracking, attention feature calculation, emotion detection, and interest prediction. All these steps are connected inside a Flask-based web application.

6.1 Data Acquisition

Webcam Capture Setup

The system uses a normal webcam to record the user's face while they watch EV design videos on the screen. The webcam is placed in front of the user at a comfortable distance so that the eyes and face are clearly visible. No special eye-tracking device is needed, which makes the system low cost and easy to use.

During each viewing session, the webcam continuously captures video frames. Users are asked to watch the EV designs naturally without special instructions so that their real viewing behaviour can be observed. Good lighting and a stable sitting position help the system track the eyes more accurately [10].

Each session runs for a fixed time so that results from different users can be compared fairly. The captured frames are then used for both eye-tracking analysis and facial emotion detection.

6.2 Face and Eye Detection
Facial Landmark Detection

After capturing the frames, the system detects the face and important facial points using computer vision. The landmark model finds key points around the eyes, eyelids, and face boundary. These points help the system understand head position and eye direction in each frame.

Correct landmark detection is important because gaze estimation depends on accurate eye location [16]. Using these landmarks, the system extracts the left and right eye regions from each frame. This removes unnecessary facial areas and allows focused analysis of eye movement and blinking.

The extracted eye regions are then used for gaze tracking and blink detection during the session.

6.3 Gaze Estimation
Gaze direction is estimated by tracking the pupil position inside the eye region. The system measures where the pupil lies relative to the eye corners and eyelids. When the pupil moves, the gaze direction also changes.

The estimated gaze is mapped onto the screen where the EV design video is shown. The screen is divided into regions so that gaze points correspond to vehicle parts such as front body, side, or interior. This mapping converts eye movement into meaningful attention data about EV design areas. Similar coordinate-based gaze tracking methods are commonly used in webcam eye-tracking systems [10], [16].

6.4 Attention Feature Extraction
The system converts gaze behaviour into simple attention measures that represent user focus on EV design regions.

Fixation Duration
Fixation duration is the time a user keeps looking at one area of the EV design. Longer viewing usually indicates stronger attention or interest. The system measures how long the gaze remains stable in one place. Fixation time is a common indicator of visual attention [9].

Blink Rate
Blink rate is calculated by detecting eye closing events over time. Frequent blinking often means reduced attention, while steady viewing suggests engagement. Blink behaviour is widely used as an attention indicator in gaze studies [20].

Focus Stability
Focus stability shows how steady the gaze remains in one region. If the gaze moves quickly across the screen, attention is unstable. If it stays concentrated, attention is stable.

Area of Interest (AOI) Attention
The EV display is divided into regions such as front, side, and interior. Each gaze point is assigned to a region. This allows the system to measure which vehicle parts receive more attention. AOI-based analysis is commonly used in design evaluation [9].

6.5 Emotion Recognition Using CNN
Along with gaze analysis, the system also detects user emotions during EV viewing. Facial images from the webcam frames are processed using a convolutional neural network trained on a Kaggle facial emotion dataset. The model recognizes expressions such as happy, neutral, sad, angry, or confused.
Emotion information supports gaze data. Focused or positive expressions usually appear during strong attention, while confused or negative expressions often occur when interest is low. Combining emotion and attention features helps the system understand user perception of EV design elements more reliably.

6.6 Graphical Attention Visualization
The system counts gaze points and fixation time for each EV region during a session. Regions with more gaze and longer viewing time indicate stronger attention.
Instead of heatmaps, the system shows results using graphs and charts such as bar charts and pie charts. These visuals display:

- gaze distribution across screen regions
- interest level proportions
- session statistics and viewing time

Graph-based visualization makes it easy to compare attention levels between EV design areas and users. Visual charts are commonly used for attention analysis [17].

6.7 Interest Classification Model

A Decision Tree classifier is used to predict user interest level in the EV design. Decision trees learn simple rules from input features, which makes them suitable for behaviour-based data.

The model uses the following input features:

- fixation duration
- blink rate
- focus stability
- AOI attention values
- detected emotion

Each viewing session produces one feature set describing user behaviour. The trained model then predicts whether the user is interested, moderately interested, or less interested based on these attention patterns. Gaze-based classification methods have been used in user preference prediction studies [17].

6.8 Flask Web Application Integration

All modules are integrated into a Flask web application. The webcam captures frames, processing modules perform gaze and emotion analysis, and the decision tree predicts interest level. The backend handles processing, while the frontend shows results and dashboards.

During operation, frames pass through face detection, gaze estimation, attention calculation, and emotion recognition. The extracted features are sent to the classifier, and predicted interest levels are displayed in real time.
The dashboard presents session statistics, gaze distribution graphs, and interest charts. This workflow provides immediate feedback on user attention while viewing EV designs and helps designers understand which vehicle features attract or lose customer interest.

RESULTS AND DISCUSSION

The proposed **AI Based Eye Tracking System for Predicting Customer Interest in EV Product Design** was tested using multiple user sessions in which participants watched EV design videos through the Flask-based web interface. During each session, the system captured real-time visual attention information such as gaze direction, blink count, and focus duration using webcam-based eye tracking.

At the same time, facial expressions were analyzed using a CNN-based emotion recognition model trained on a Kaggle facial emotion dataset to identify emotions such as happy, neutral, confused, sad, and angry. These attention and emotion features were combined and processed using a Decision Tree classifier to estimate user interest levels as interested, moderately interested, or less interested. The results were displayed on graphical dashboards showing session statistics, gaze distribution, and interest classification.

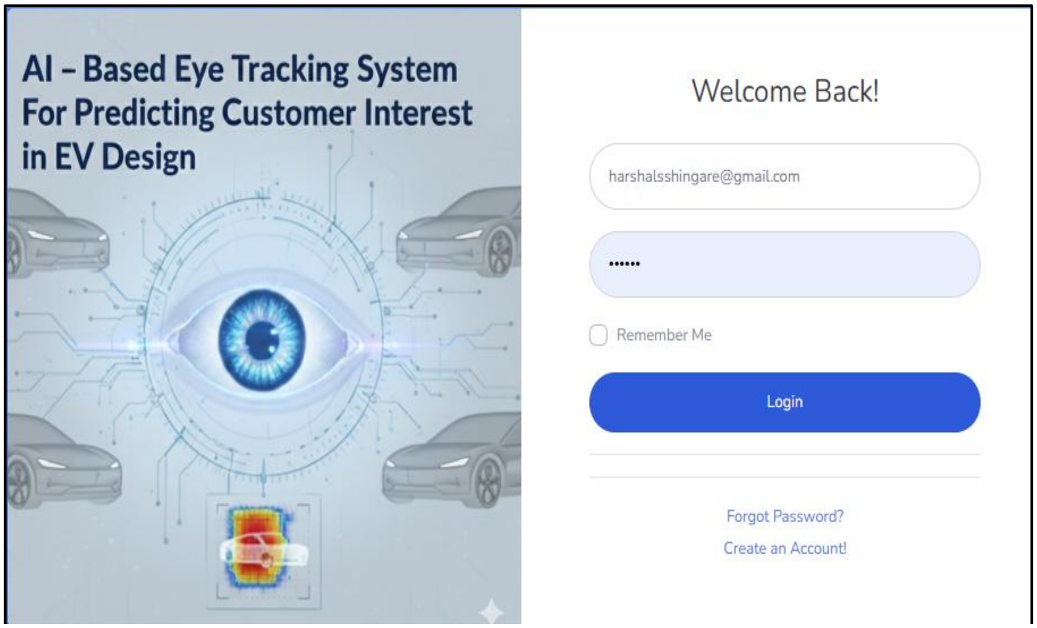

Fig. 2. Login interface

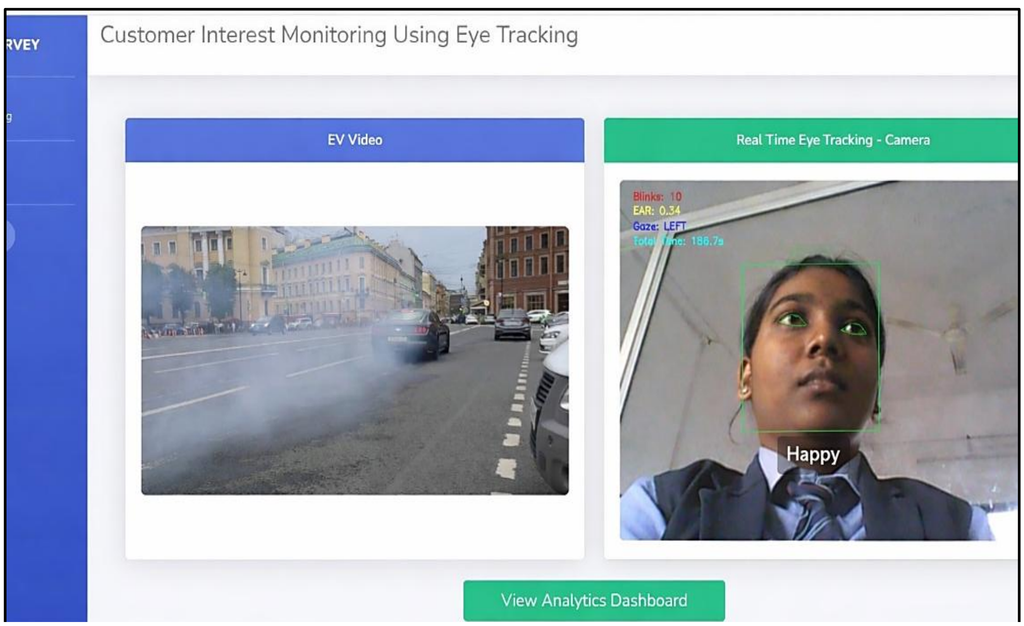

Fig. 3. Real-time eye tracking and emotion detection

7.1 Session Statistics and Viewing Behaviour

According to the dashboard, a total of 11 user sessions were recorded with an average watch time of about 45.45 seconds and a total analysis time of around 499.94 seconds. It was also noticed that as more sessions were conducted, the average watch time slightly increased. This suggests that users spent more time observing the EV designs in later sessions, which may indicate growing familiarity and better engagement with the content.

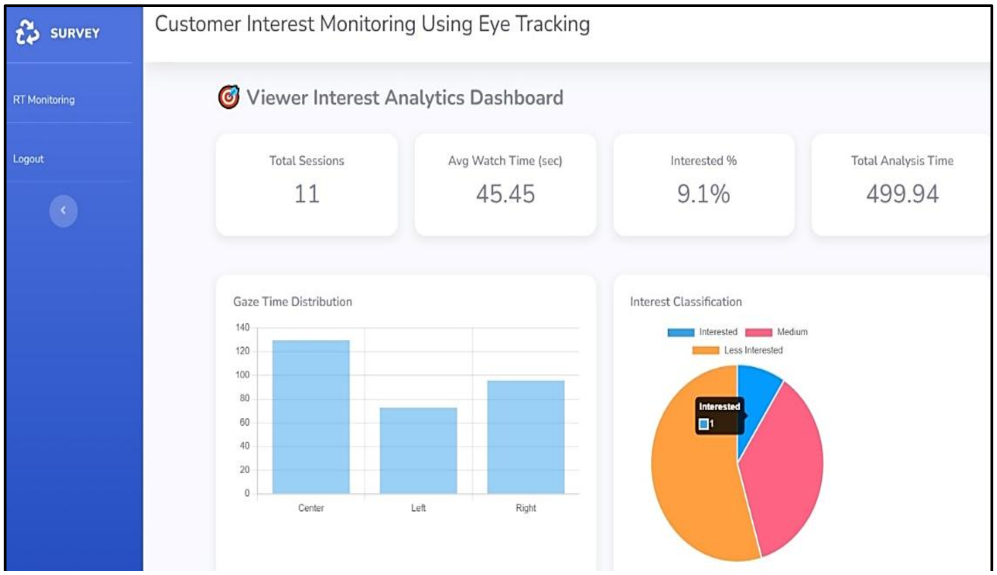

Fig. 4. Viewer interest analytics dashboard

7.2 Gaze Distribution Analysis

The gaze distribution graph shows that users spent the most viewing time in the center region of the EV display compared to the left and right regions. This means that the main vehicle features placed in the center naturally attracted more attention. The side regions received less viewing time, indicating lower visual focus. This pattern shows that gaze location can clearly indicate which parts of the EV design attract user attention.

7.3 Interest Classification Results

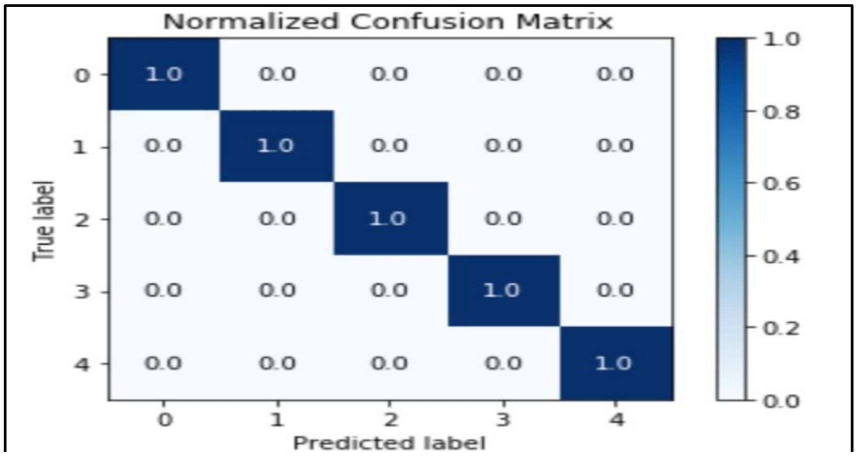

Fig. 5. Normalized confusion matrix

The interest classification chart indicates that most viewing instances were labeled as moderately interested or less interested, while a smaller portion was classified as highly interested. This suggests that only certain EV design elements strongly captured user attention. Regions with longer gaze duration and steady focus were more often classified as interested, whereas areas with shorter viewing time and frequent gaze movement were classified as less interested. This confirms that eye-tracking-based attention features can effectively differentiate levels of user interest.

7.4 Emotion-Based Engagement Analysis

Emotion recognition results also supported the interest prediction. Sessions with higher interest levels often showed neutral or happy facial expressions along with longer gaze duration and fewer blinks. In contrast, confused or disengaged expressions appeared more frequently in sessions with lower interest scores. This shows that combining gaze behaviour with facial emotion gives a clearer picture of user engagement than using eye tracking alone.

7.5 Blink Behaviour and Attention Relationship

Blink behaviour analysis further supported the attention results. Users showed fewer blinks when they were steadily focused on EV features, while higher blink rates appeared when attention decreased or shifted. This connection between blinking and attention helped the Decision Tree model distinguish interest levels more accurately and improved prediction reliability.

7.6 Overall System Performance

Overall, the graphical dashboard provided clear and easy-to-understand information about user attention and emotional response while viewing EV designs. Unlike traditional surveys, the system uses actual viewing behaviour captured in real time. The results show that combining eye tracking, emotion recognition, and machine learning can successfully estimate customer interest and identify which EV design areas attract or lose attention. These findings can help designers improve EV product appearance and support design decisions based on real user behaviour.

CONCLUSION

This paper presented an **AI Based Eye Tracking System for Predicting Customer Interest in EV Product Design** that studies how users react to electric vehicle designs through their visual attention and facial expressions. The system uses a normal webcam to capture eye gaze, blink rate, facial landmarks, and focus duration while users watch EV design videos. At the same time, facial expressions are analysed using a CNN model trained on a public emotion dataset to identify emotions such as happy, neutral, or confused. These attention and emotion features are then processed using a Decision Tree model to classify user interest as interested, moderately interested, or less interested.

The results showed that users spent more time looking at important vehicle areas, especially the front and central design parts. These regions had longer focus time, steady gaze, and fewer blinks, which indicates stronger attention. The model was able to classify interest levels based on these patterns, showing that real viewing behaviour can reflect customer interest. The Flask-based dashboard displayed session details, gaze distribution, and interest levels using charts and graphs in real time, making the results easy to understand.
The system works without special hardware, which makes it affordable and suitable for industrial use. Compared to surveys, this approach captures real behaviour instead of opinions, providing more reliable feedback for designers. Overall, the system offers a simple and practical way to evaluate EV designs before production.

There is still room for improvement. The current system uses a limited dataset and a basic Decision Tree model. In the future, larger datasets and more advanced models can improve accuracy. Performance can also be enhanced under different lighting conditions and head movements. The system can further be extended to compare multiple EV designs or support more users at the same time. With further development, this approach can also be applied to other product design fields.

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