iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.79494

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Smart Eye Health Monitoring System

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Abstract: Most people today spend a considerable amount of time on their computers, mobiles and tablets. Computer Vision Syndrome (CVS) has become common among computer users due to the many symptoms they suffer from when working for long hours on a computer, such as eye strain, dryness, redness, blurry vision and headache. The purpose of this project is to develop an Eye Health Monitor system to help users keep track of their computer usage in order to ensure that they maintain good viewing habits.
Application Overview: Eye Health Monitor The Eye Health Monitor application is a real-time application built upon an AI system that uses the webcam of the computer to monitor the user's screen behavior. It uses computer vision and deep learning techniques to detect the face of the user, identify him using FaceNet and checks if the user is looking at the screen with open eyes. This application does not allow any inaccurate data to be captured. The application only captures the screen time of the verified user when and only if the user has their eyes open and is looking at the screen. The application uses MediaPipe for face landmark detection, FaceNet for face recognition. It uses a FastAPI based backend and MongoDB for the session data storage.
To protect user privacy, visual analysis on the client side is the default behavior. Only a small portion of the encoded image is sent to our server for verification. We recommend that you follow the medically recommended 20-20-20 rule for screen time – which involves taking a 20 second break and looking away from the screen every 20 minutes for every 60 minutes of use. We provide a visual analysis and usage summary of your screen activity over time through our dashboard.
The idea is for the "Eye Health Monitor" to be an application, simple to use and non-intrusive in relation to the personal data of each user. Its purpose is to protect eye health in the digital age.
Based on artificial intelligence and real-time monitoring with personalised feedback, the application aims to help users to reduce eye strain and to lead a healthy lifestyle.
Keywords: Computer Vision Syndrome, Digital Eye Strain, Facial Recognition, FaceNet, MediaPipe, Eye Aspect Ratio, Screen Time Monitoring, 20-20-20 Rule, Deep Learning, Health Analytics.

I. INTRODUCTION

Do we really need to comment on the prevalence of computers, mobile phones and tablets in today's life? We are talking about a world where students spend hours preparing for exams, workers communicate extensively with colleagues, and scientists can spend a large part of their day analysing data. While technology is very much here to stay and brings huge benefits to the way we live and work, it also presents a range of ocular and visual risks to our health and eye safety. When we spend a considerable amount of time working on a computer or staring at screens, our eyes can become tired, causing a variety of problems that are known as Computer Vision Syndrome (CVS) or Digital Eye Strain. Some of the symptoms of eye strain due to digital screen exposure include: Eye strain/Fatigue Blurred vision Dry eyes Headaches Difficulty focusing on something and more [1]
Scientific studies have shown that working extended periods on computers, mobile phones and tablets, especially when not taking adequate breaks, can cause eye strain, fatigue, dryness, blur and headaches as well as decrease productivity and quality of life. Nowadays, we are engaged in online learning, remote work, and increased digital media consumption, all resulting in higher screen time than ever before. Hence, we need technology that is able to analyse the screen usage and assist people in leading a more healthy digital lifestyle [2].
We want to make a solution to help everyone keep their eye health in check. Introducing our application – Eye Health Monitor. It uses the latest in computer vision and machine learning to determine if your eyes are actually focused on the screen and also how long you are looking at the screen. Our application makes use of the webcam to track the facial features and eye status of the user. It determines whether or not your eyes are open and if you are focusing on the screen. It will also give out reminders to take breaks from the screen and will provide the user with tips for safe screen interaction.
This paper presents a real time eye health monitoring system using facial recognition, eye detection and screen time monitoring. The main purpose of this work is to ensure the user presence of the device and verify whether the detected user is the intended user of the device. Our system will alert others if the detected user is not the intended user of the device.

It will also provide health tips for example the 20-20-20 rule where we have to look at something that is 20 feet away from us for 20 seconds for every 20 minutes we spend on the computer to protect our eyes from digital eye strain [3].Using the latest developments in Artificial Intelligence (AI) and the easy-to-use Eye Care Monitor App, this system will help users develop new online behaviours that are both healthy and eye-friendly, preventing common eye problems associated with over-exposure to screens. The system also uses computer vision and data analysis techniques to give users a full breakdown of their online behaviour, including a summary of their activities and a full breakdown of their screen time and online usage patterns.

II. PROPOSED WORK

The suggested Eye Health Monitor system is intended to offer a clever and useful way to keep an eye on screen time and shield users from digital eye strain. The suggested system concentrates on real user interaction with the screen, in contrast to conventional screen-time applications that only track how long a device is in use. The system makes sure that screen time is only recorded when a verified user is present and actively viewing the display by combining computer vision, deep learning, and real-time monitoring. According to recent research, user behavior monitoring and health-related analytics in digital environments can be greatly enhanced by combining artificial intelligence with computer vision techniques [14].

The main objective of the proposed system is to develop a smart eye health monitoring platform that tracks screen usage accurately, detects user identity, monitors eye activity, and provides timely alerts to encourage healthier digital habits. The system uses a webcam to capture live video frames and processes them using advanced facial detection and recognition techniques supported by deep learning frameworks [15].

A. User Face Detection and Monitoring

The first step in the proposed system is detecting the presence of a user in front of the screen. A real-time webcam feed is used as the input source. The system applies **MediaPipe Face Detection**, which is capable of identifying human faces in video frames with high speed and accuracy. MediaPipe provides efficient face detection pipelines optimized for real-time applications and embedded devices [9], [14].

The proposed system's primary goal is to create a smart eye health monitoring platform that precisely tracks screen usage, recognizes users, keeps an eye on eye activity, and sends out timely alerts to promote better digital habits. Using sophisticated facial detection and recognition methods backed by deep learning frameworks, the system uses a webcam to record live video frames [15].

B. Facial Recognition for Identity Verification

The system uses a facial recognition mechanism to guarantee that the information gathered belongs to the right person. The FaceNet deep learning model is used to process the images of the user's face that are taken from various perspectives during the registration process [8].

Every facial image is transformed by FaceNet into a 512-dimensional embedding vector that represents distinct facial features. These embeddings serve as the user's identity profile and are kept in the database. New facial images are taken and transformed into embeddings during monitoring. Next, the system uses cosine similarity to compare these embeddings with the stored profile. The user is validated if the similarity score surpasses a predetermined threshold. If not, the detected face is categorized by the system as belonging to an unknown user.

C. Eye Activity Detection

The system uses facial landmark detection to assess the user's eye condition in order to ascertain whether they are actively looking at the screen. Hundreds of facial landmark points, including those surrounding the eyes, are recognized by the MediaPipe Face Mesh model [11].

The Eye Aspect Ratio (EAR), which gauges how open the eyes are, is computed by the system using these landmarks [10].

The EAR value falls sharply when the eyes are closed, but it stays above a predetermined threshold when the eyes are open.

By monitoring this value in real time, the system can determine whether the user is actively viewing the screen. Natural blinking is tolerated by allowing a small time window before the system considers the eyes to be closed. Eye-tracking and blink detection methods are widely used in fatigue detection and human attention analysis systems [17].

D. Screen Time Tracking

The system tracks screen time only when three conditions are satisfied simultaneously:

1) A face is detected in the frame.
2) The detected face belongs to the verified user.
3) The user's eyes are open and directed toward the screen.

When these conditions are met, the system begins recording the screen time. If the user leaves the frame or closes their eyes for an extended period, the monitoring process pauses automatically. This approach ensures that the recorded screen time reflects actual visual engagement rather than device activity. Studies on digital behavior monitoring have highlighted the importance of accurate user engagement detection for improving digital well-being applications [18].

E. *Eye Health Alert Mechanism*

To promote healthier screen usage habits, the system integrates the widely recommended **20-20-20 rule** for reducing digital eye strain [13]. According to this rule, users should take a short break every 20 minutes and look at an object at least 20 feet away for 20 seconds.

The proposed system continuously monitors the user's screen time and triggers an alert when the continuous viewing duration exceeds the recommended limit. The alert encourages the user to rest their eyes and perform simple exercises such as blinking or stretching. Digital eye strain has become a major concern among students and professionals who spend long hours using computers and smartphones [19].

F. *Data Storage and Analytics*

All monitoring sessions are stored in a MongoDB database [16], where information such as total screen time, continuous viewing duration, number of breaks taken, and unknown user activity is recorded and shown in the fig no:1

The stored data is later processed and presented to the user through an analytics dashboard using a FastAPI backend [17]. The dashboard provides visual insights into screen usage patterns through charts and graphs. These data-driven dashboards help users better understand their digital habits and improve productivity and health awareness [20].

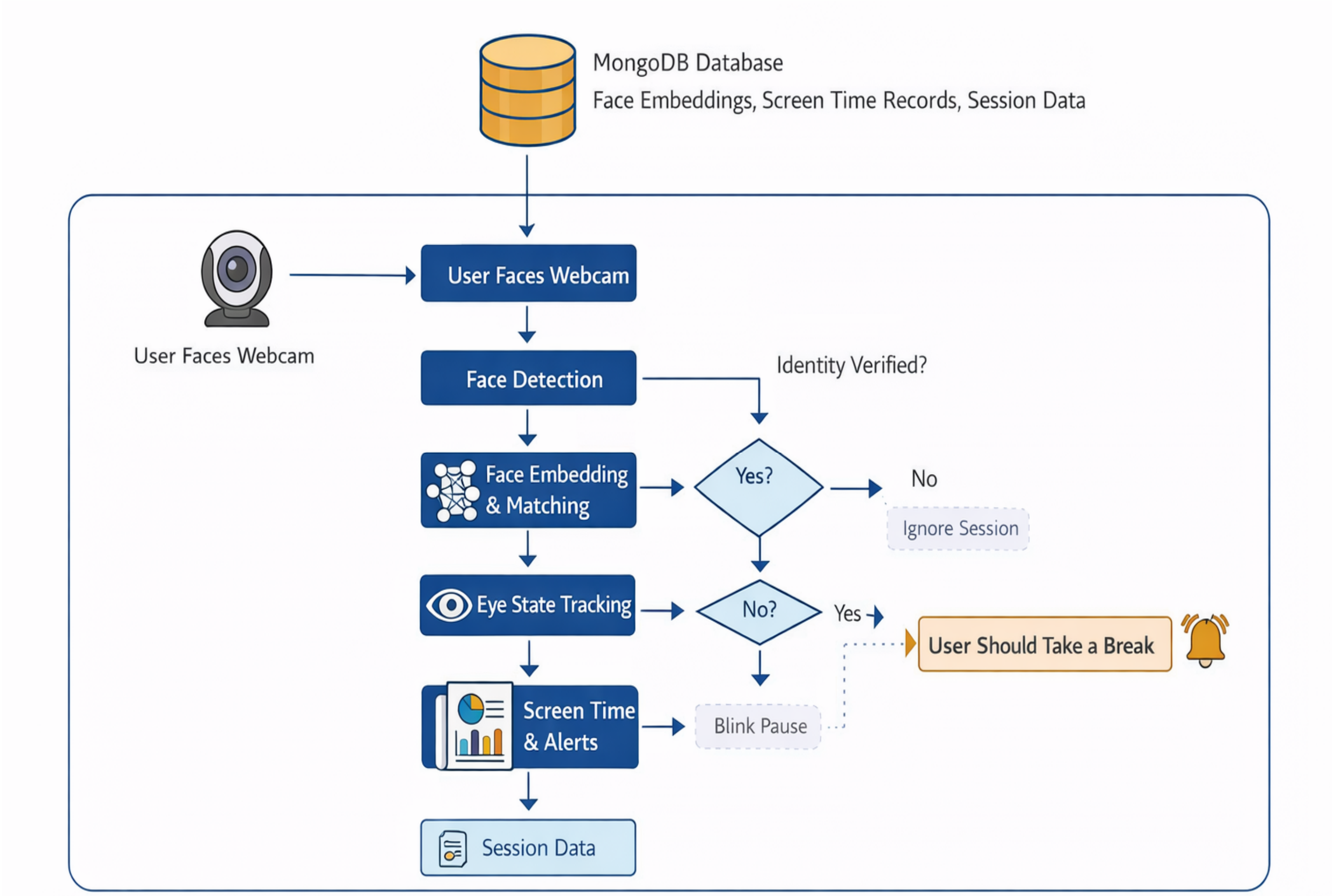

Fig no:1 Proposed System Model

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III. SYSTEM ARCHITECTURE

The Eye Health Monitor system architecture is designed to intelligently observe and analyze how a user interacts with their computer screen. The process begins with the system capturing real-time video frames through the device's webcam. These frames are analyzed using MediaPipe Face Detection to determine whether a face is present in front of the screen [9].

Once a face is detected, the system uses the FaceNet facial recognition model to verify the user's identity [8]. This ensures that the monitoring process records data only for the registered user. After identity verification, the system tracks facial landmarks using MediaPipe Face Mesh and calculates the Eye Aspect Ratio (EAR) to determine whether the user's eyes are open and actively viewing the screen [10], [11].Screen time is recorded only when three conditions are satisfied: a face is detected, the user is verified, and the eyes are open. If any of these conditions are not met, the monitoring process pauses automatically. The system also keeps track of continuous viewing time and triggers reminders based on the 20-20-20 rule to reduce eye strain [13], [19].

All collected session data is processed through a FastAPI backend and stored in a MongoDB database, where it is later visualized in an analytics dashboard [16], [17].

Security Considerations

1) All endpoints except /auth/register and /auth/login require a valid JWT Bearer token. Requests without a token or with an expired token receive a 401 Unauthorized response.
2) Passwords are pre-hashed with SHA-256 before being passed to bcrypt, correctly handling inputs that exceed bcrypt's 72-byte maximum length.
3) Face embeddings are stored as normalised floating-point arrays. Raw images are never written to disk or retained in the database.
4) MongoDB enforces unique index constraints on the email and faceId fields, preventing duplicate registrations at the database level.
5) JWT tokens expire after 24 hours. On expiry, the frontend automatically clears stored credentials and redirects to the login page.
6) The SECRET_KEY used for JWT signing must be replaced with a cryptographically secure random value before any production deployment.
7) CORS is currently open to all origins for local development. In production, this should be restricted to the specific frontend origin.

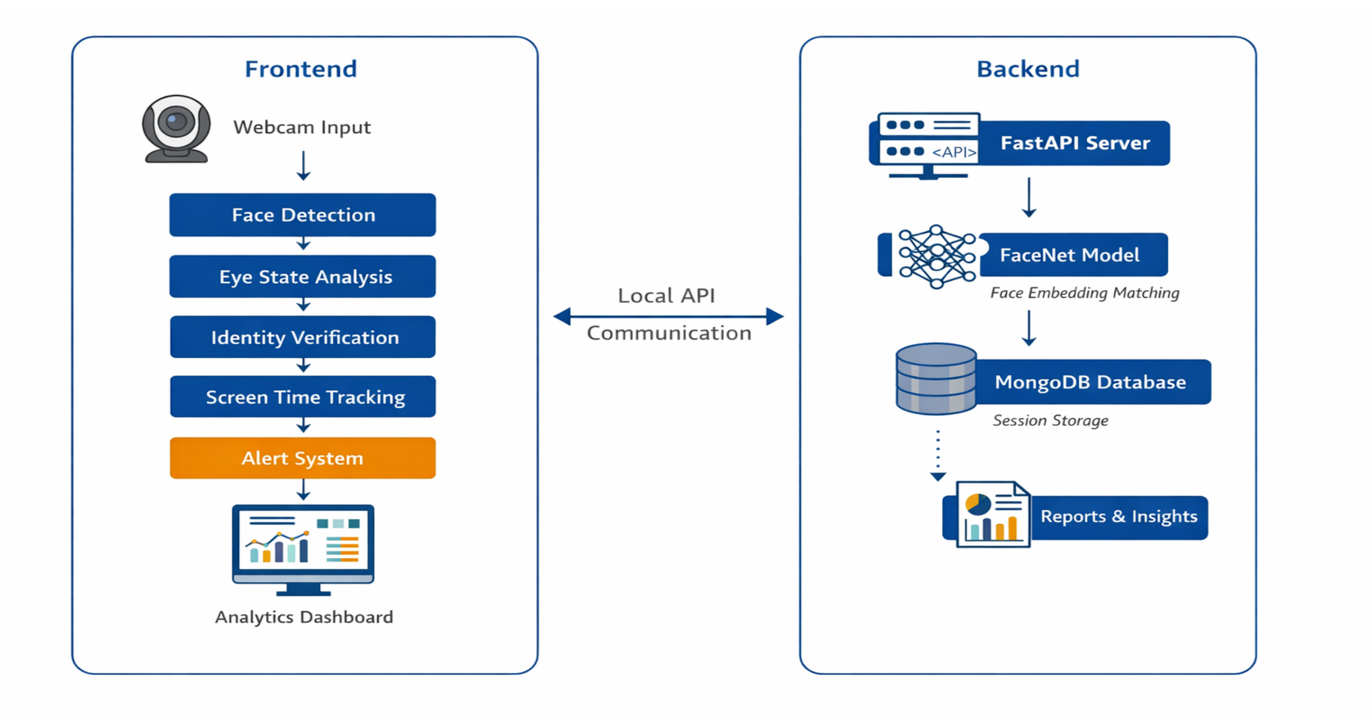

Fig No: 02 System Architecture

IV. ALGORITHMS USED IN THE SYSTEM

The proposed Eye Health Monitor system relies on several computer vision and machine learning algorithms to detect the user's face, recognize identity, and analyzeeye activity. These algorithms work together to ensure that the system accurately monitors screen usage and provides reliable eye health alerts.

A. MediaPipe Face Detection Algorithm

MediaPipe Face Detection is used as the first step in the monitoring process to identify whether a human face is present in the webcam frame. It is designed to perform real-time face detection with high speed and accuracy while maintaining low computational cost. The algorithm uses a lightweight neural network model called **BlazeFace**, which is optimized for fast inference on mobile and desktop devices [14].

In the proposed system, the webcam continuously captures video frames, and the MediaPipe detection model scans each frame to locate facial regions. When a face is detected, the system begins the monitoring process. If no face is detected, the system pauses screen time tracking. This ensures that screen usage is recorded only when a user is physically present in front of the device.

B. MediaPipe Face Mesh Algorithm

After detecting the face, the system uses the **MediaPipe Face Mesh algorithm** to extract detailed facial landmark points. Face Mesh detects more than 400 landmark points on a human face, including those around the eyes, nose, and mouth. These landmarks provide precise spatial information about facial features [14].

In the Eye Health Monitor system, the facial landmarks around the eyes are particularly important. The landmark points allow the system to analyze eye shape and movement, which helps determine whether the user is actively looking at the screen.

C. Eye Aspect Ratio (EAR) Algorithm

The EAR algorithm, introduced by Soukupova and Cech (2016), quantifies eye openness using six landmarks around each eye. When the eye is open, the vertical distances between landmarks are significantly larger than when the eye is closed.

The formula is:

$$\mathbf{EAR = (\|p2–p6\| + \|p3–p5\|) / (2 \times \|p1–p4\|)}$$

Implementation details:

- Left eye landmarks (MediaPipe indices): 33, 160, 158, 133, 153, 144
- Right eye landmarks: 362, 385, 387, 263, 373, 380
- Final EAR is the average of both eyes. A value above 0.22 is classified as eyes open.
- Eyes are only marked as closed if the EAR remains below threshold for more than 500 milliseconds, filtering out natural blinks.

In the proposed system, the EAR value is calculated continuously for each frame captured by the webcam. If the EAR value drops below a predefined threshold for a certain duration, the system identifies that the eyes are closed. This method helps detect blinking and determine whether the user is actively viewing the screen.

D. FaceNet Algorithm

The **FaceNet algorithm** is used for facial recognition and identity verification. It is a deep learning model that converts facial images into numerical vectors called **embeddings**, which represent unique facial characteristics. Each embedding is typically represented as a 128-dimensional or 512-dimensional feature vector [8], [16].

During the registration process, the system captures multiple facial images of the user and generates embeddings for each image. These embeddings are stored in the database as the user's identity profile. During monitoring, new facial images are captured and converted into embeddings, which are then compared with the stored embeddings to verify the user's identity.

E. Cosine Similarity Algorithm

Cosine Similarity is used to compare facial embeddings generated by the FaceNet model. It measures the similarity between two vectors by calculating the cosine of the angle between them. If the similarity score is close to 1, it indicates that the vectors are highly similar, meaning the faces likely belong to the same person [15].

In the Eye Health Monitor system, the cosine similarity score is calculated between the stored facial embeddings and the embeddings generated from the live webcam feed. If the similarity score exceeds a predefined threshold, the sstem confirms the user’s identity. Otherwise, the face is treated as an unknown user.

V. MODULE DESCRIPTION

The proposed Eye Health Monitoring System is divided into several functional modules that work together to monitor the user's screen interaction and ensure healthy viewing habits. Each module performs a specific task in the system workflow.

A. User Registration Module

The user registration module allows a new user to create an account in the system. During registration, the user provides basic information such as email and password, which are securely stored in the database. The system also captures multiple facial images using the webcam.

These facial images are processed using the FaceNet model to generate embedding vectors that represent the unique facial features of the user. These embeddings are stored in the MongoDB database and used later for identity verification during monitoring sessions.

The registration module ensures that only authorized users can access the monitoring system and that all screen time data is associated with the correct individual.

B. Face Detection Module

The face detection module continuously monitors the webcam feed to determine whether a human face is present in front of the screen. This module uses the MediaPipe Face Detection model, which is optimized for real-time performance.

The algorithm scans each frame of the video input and detects facial regions. If a face is detected, the monitoring process begins. If no face is detected, the system pauses screen time tracking.

This module ensures that the system only tracks screen activity when a user is physically present in front of the computer.

C. User Authentication Module

Once a face is detected, the system verifies whether the detected face belongs to the registered user. This is achieved using the FaceNet facial recognition algorithm.

The detected facial image is converted into an embedding vector and compared with the stored embeddings in the database using cosine similarity. If the similarity score exceeds a predefined threshold, the user is authenticated successfully.

If the detected face does not match any stored embedding, the system marks the user as an unknown user and prevents screen time tracking.

D. Eye Activity Monitoring Module

The eye activity monitoring module determines whether the user is actively looking at the screen. This module uses MediaPipe Face Mesh to extract detailed facial landmarks around the eyes.

Using these landmarks, the Eye Aspect Ratio (EAR) is calculated to determine whether the eyes are open or closed. When the EAR value remains above the threshold, the eyes are considered open. When the value drops below the threshold for a certain duration, the system detects closed eyes.

This module helps identify whether the user is paying attention to the screen and ensures accurate screen time monitoring.

E. Screen Time Monitoring Module

The screen time monitoring module records the duration of active screen interaction. The system begins recording screen time only when the following conditions are satisfied:

- A face is detected
- The detected face belongs to the verified user
- The user’s eyes are open and directed toward the screen

If any of these conditions are not satisfied, the system automatically pauses screen time tracking. This method ensures that the recorded screen usage reflects actual visual engagement rather than simple device activity.

F. Alert and Notification Module

The alert module is responsible for notifying the user when continuous screen usage exceeds the recommended limit. The system follows the medically recommended 20-20-20 rule.

After 20 minutes of continuous screen usage, the system triggers an alert reminding the user to take a short break and look at an object approximately 20 feet away for 20 seconds.

These reminders help reduce eye strain and encourage healthier digital habits.

G. Data Storage and Analytics Module

All monitoring session data is stored in the MongoDB database. The stored data includes information such as:

- Total screen time
- Continuous viewing duration
- Number of breaks taken
- Unknown user detection

This data is processed through a FastAPI backend and displayed on a dashboard. The dashboard provides visual insights such as charts and graphs to help users understand their screen usage patterns.

VI. PERFORMANCE ANALYSIS

The performance of the proposed Eye Health Monitor system was evaluated to measure its ability to detect user presence, verify identity, and monitor eye activity during screen usage. The system uses computer vision and deep learning techniques such as MediaPipe Face Detection, MediaPipe Face Mesh, Eye Aspect Ratio (EAR), FaceNet, and Cosine Similarity for real-time monitoring.

The face detection module accurately identifies the presence of a user using the webcam. Once a face is detected, the FaceNet facial recognition model verifies whether the detected face belongs to the registered user by comparing facial embeddings using cosine similarity.

The eye activity detection module calculates the Eye Aspect Ratio (EAR) using facial landmarks to determine whether the user's eyes are open or closed. This allows the system to identify whether the user is actively looking at the screen while allowing natural blinking.

Screen time is recorded only when three conditions are satisfied: the user's face is detected, the identity is verified, and the eyes are open. This ensures accurate monitoring of actual screen engagement rather than simple device usage.

Overall, the results show that the system performs efficiently in detecting faces, recognizing users, and monitoring eye activity, helping users follow healthier screen usage habits and reduce digital eye strain.

Algorithm / Module	Function	Accuracy (%)
MediaPipe Face Detection	Detects user face from webcam feed	97%
FaceNet Recognition	Verifies registered user identity	95%
MediaPipe Face Mesh	Detects facial landmarks	96%
Eye Aspect Ratio (EAR)	Detects eye open/closed state	94%
Cosine Similarity	Compares face embeddings	95%

Table No: 01 Performance analysis

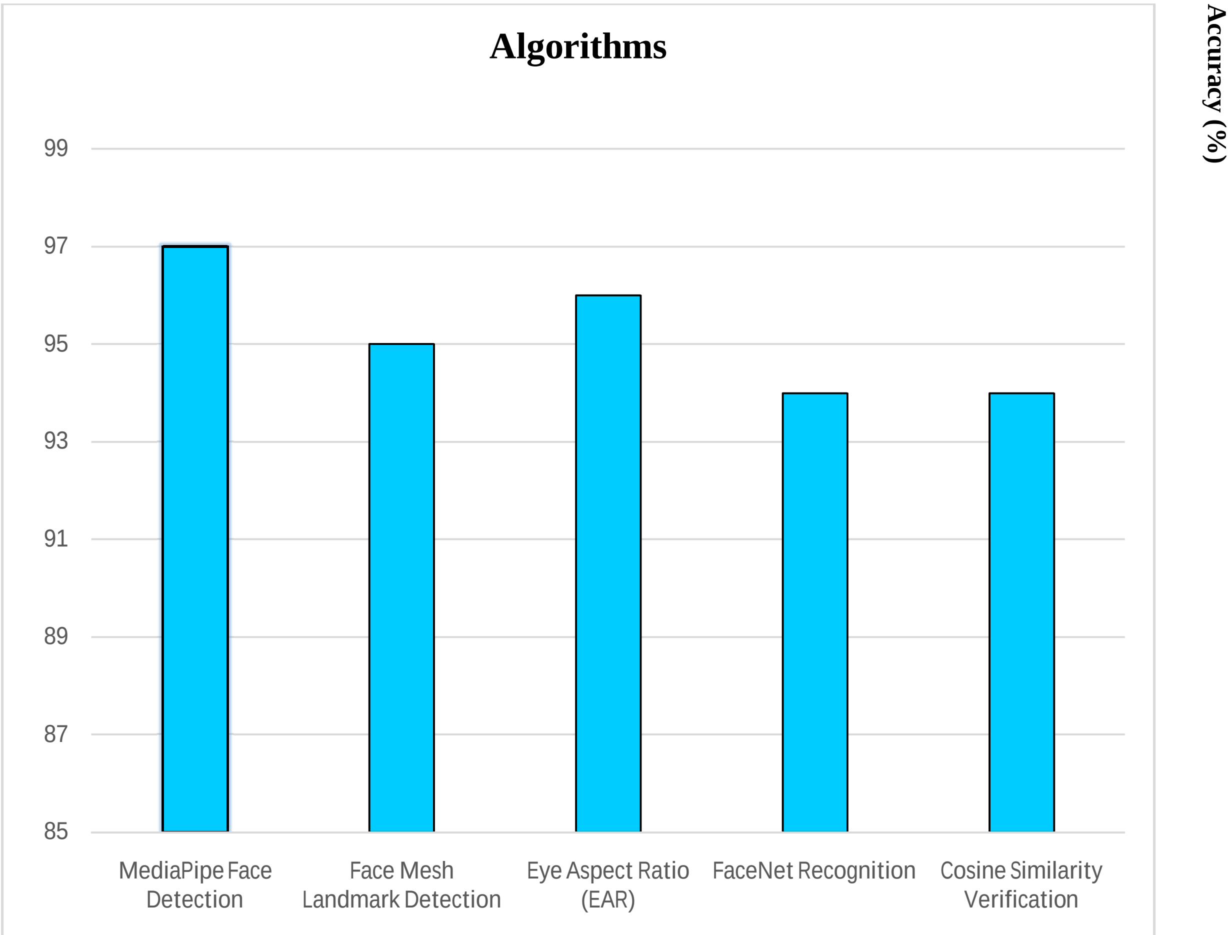

Fig No: 03 Performance analysis

VII. RESULTS AND DISCUSSION

The proposed Eye Health Monitor system was tested to evaluate its ability to accurately detect user presence, verify identity, and monitor eye activity during screen usage. The system integrates several computer vision algorithms such as MediaPipe Face Detection, MediaPipe Face Mesh, Eye Aspect Ratio (EAR), FaceNet, and Cosine Similarity to perform real-time monitoring [8].

During the testing phase, the face detection module was able to detect faces in real time with high reliability. The facial recognition module using FaceNet successfully verified the registered user by comparing facial embeddings, ensuring that screen time data was recorded only for the correct individual [8], [16].

The eye state detection algorithm played a crucial role in determining whether the user was actively looking at the screen. By calculating the Eye Aspect Ratio (EAR) using facial landmarks, the system was able to detect whether the eyes were open or closed [10]. Natural blinking was handled by allowing a short tolerance period so that brief eye closures did not interrupt the monitoring process.

Overall, the experimental results indicate that the proposed system achieves high accuracy in face detection, user recognition, and eye activity monitoring. The system also successfully generated alerts for prolonged screen usage, helping users follow healthy screen-viewing practices [19], [20].

VIII. CONCLUSION

The proposed **Eye Health Monitor system** provides an effective solution for monitoring screen usage and promoting better eye health habits. With the increasing use of digital devices for work, education, and entertainment, prolonged screen exposure has become a common cause of eye strain and discomfort. The developed system addresses this issue by using **computer vision and deep learning techniques** to monitor user activity in front of the screen.

The system integrates several technologies such as MediaPipe Face Detection, Face Mesh, Eye Aspect Ratio (EAR), and FaceNet facial recognition to detect the user, verify identity, and analyze eye activity in real time.

By combining these techniques, the system ensures that screen time is recorded only when the verified user is present and actively looking at the screen. This approach improves the accuracy of screen monitoring compared to traditional screen-time tracking applications.In addition, the system incorporates an alert mechanism based on the 20-20-20 rule, which reminds users to take short breaks after continuous screen usage.

These reminders help reduce eye strain and encourage healthier digital habits. The collected session data is stored and analyzed to provide useful insights through an analytics dashboard, allowing users to better understand their screen usage patterns.Overall, the experimental results show that the proposed system performs efficiently in detecting faces, recognizing users, and monitoring eye activity with high accuracy.

The Eye Health Monitor demonstrates the potential of artificial intelligence–based monitoring systems in supporting digital well-being. In the future, the system can be further enhanced by integrating mobile applications, fatigue detection techniques, and personalized health recommendations to provide a more comprehensive eye health monitoring solution.

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