## EYE EASE DETECTION SYSTEM USING ML

*A project report submitted in partial fulfilment of the requirements for the award of the degree of*

### Bachelor of Technology

in

### Department of CSE-Artificial Intelligence and Machine Learning

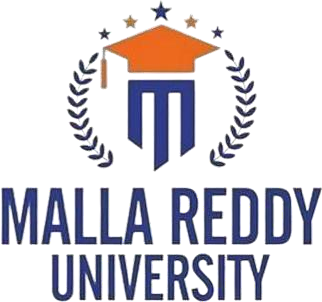
*Submitted By*

|  |  |
| --- | --- |
| **M Adieshwar Reddy** | **(2311CS020426)** |
| **Md.Farhaan** | **(2311CS020427)** |
| **Md.Harshath** | **(2311CS020428)** |
| **Dh.Bhaskhar** | **(2311CS020429)** |
| **I.Kruthika** | **(2311CS020430)** |
|  |  |

Under the esteemed guidance of

### Prof .A.Vineela

### Associate Professor



**Department of Artificial Intelligence and Machine Learning School Of Engineering**

## MALLAREDDY UNIVERSITY

Masiammaguda, Dulapally, Hyderabad, Telangana–500100

**2025**



# Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning)

**CERTIFICATE**

This is to certify that the project report entitled **“Eye Ease Detection System   
Using ML”** submitted by **M.Adieshwar Reddy(2311CS020426) ,Md.Farhaan (2311CS020427) , Md.Harshath (2311CS020428), Dh.Jitendra Sai Bhaskar (2311CS020429) , I.Kuthika Sai Sree (2311CS020430)** towards the partial fulfilment of the award of Bachelor’s Degree in Project Development from the Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Malla Reddy University, Hyderabad, is a record of bonafide work done by him. The results embodied in the work are not submitted to any other University or institute forward of degree or diploma.

|  |  |  |
| --- | --- | --- |
| **INTERNALGUIDE** | **HOD** | **DEAN** |
| **Prof. A Vineela**  **Associate Professor** | **Dr. R Nagaraju CSE(AI& ML)** | **Dr. G Gifta Jerith CSE(AI&ML)** |

**EXTERNALEXAMINER**

## DECLARATION

I hereby declare that the project report entitled “Eye Ease Detection Using ML” has been carried out by us and this work has been submitted to the Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Malla Reddy University, Hyderabad in partial fulfilment of the requirements for the award of degree of Bachelor of Technology.I further declare that this project has not been submitted in full or part for the award of any other degree in any other educational institutions.

Place:Hyderabad Date: 29/03/25

|  |  |  |
| --- | --- | --- |
| **Name** | **RollNumber** | **Signature** |
| M.Adieshwar Reddy  Md.Farhaan  Md.Harshath  Dh.Bhaskhar    I.Kruthika Sai Sree | 2311CS020426    2311CS020427  2311CS020428  2311CS020429  2311CS020430 |  |
|  |  |  |

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M Adieshwar (2311CS020426)

Md Farhaan (2311CS020427)   
Md Harshath (2311CS020428)

Dh Bhaskar (2311CS020429)

I Kruthika (2311CS020430)

**Abstract**

Fatigue driving is one of the major causes of road accidents and death. Hence, detection of driver’s fatigue and its indication is an active research area. Most of the conventional methods are either vehicle based, or behavioural based or physiological based. Few methods are intrusive and distract the driver, some require expensive sensors and data handling. Therefore, in this study, a low cost, real time driver’s drowsiness detection system is developed with acceptable accuracy. In the developed system, a webcam records the video and driver’s face is detected in each frame employing image processing techniques. Facial landmarks on the detected face are pointed and subsequently the eye aspect ratio, mouth opening ratio and nose length ratio are computed and depending on their values, drowsiness is detected based on developed adaptive thresholding. Machine learning algorithms have been implemented as well in an offline manner. A sensitivity of 95.58% and specificity of 100% has been achieved in Support Vector Machine based classification. This feature is used for the safety of the peoples from the accidents. This work shows the development of ADAS (advance driving assistance system) this focus on the driver drowsiness detection is main aim to alert the driver from the drowsiness state to avoid road accidents. In this we use the Machine Learning to predict the condition and emotions of the driver that will improve the safety on the roads. We use the CNN for this project that will effectively detect the driver fatigue status using driver images. In this project we can use the Electrocardiogram (ECG) for the psychological system to detect drowsiness. Artificial Intelligence means system can automatically learns as well as improve without being programmed. We also use the various machine learning techniques like OpenCV, Keras, Tensorflow.

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## CHAPTER1:INTRODUCTION

* 1. **Problem Definition**

Fatigue driving is a major contributor to road accidents, resulting in significant injuries and fatalities. Despite various existing methods for detecting driver drowsiness, many are intrusive, expensive, or require complex setups. The need for a non-intrusive, cost-effective, and real-time solution to detect driver drowsiness is paramount. This project aims to develop a low-cost, real- time driver drowsiness detection system that uses image processing and machine learning techniques to monitor driver alertness through facial landmarks. The system will provide timely alerts to prevent accidents caused by driver fatigue, thereby enhancing road safety.

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* 1. **Objective of the Project**

The primary objective of this project is to develop an Advanced Driver Assistance System (ADAS) that accurately detects driver drowsiness and issues real-time alerts. The system leverages a webcam to capture video, processes facial landmarks to compute metrics like eye aspect ratio, and employs adaptive thresholding to detect drowsiness. Additionally, machine learning algorithms, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), are used to enhance detection accuracy. By achieving a balance between cost- effectiveness and precision, the project aims to reduce the incidence of road accidents due to driver fatigue.

* 1. **Limitations of the Project**

Detecting eye fatigue using machine learning has several limitations, including:

**Data Availability and Quality:** Obtaining large, diverse, and accurately labeled datasets for training can be challenging. The quality of the data can affect the performance of the model

**Subject Variability:** Individuals may exhibit different patterns of eye fatigue, making it difficult to develop a one-size-fits-all model. Factors such as age, gender, and underlying health conditions can also contribute to variability.

**Real-time Processing:** Achieving real-time eye fatigue detection can be computationally intensive, especially when processing high-resolution video streams. This can be a limitation for applications requiring low latency.

**Hardware Requirements:** Implementing eye fatigue detection systems may require specialized hardware, such as high-resolution cameras or infrared sensors, which can increase the cost and complexity of the system.

**Environmental Factors:** Ambient lighting conditions, screen glare, and other environmental factors can affect the accuracy of eye fatigue detection algorithms, requiring robustness to such variations.

**Generalization to Other Tasks:** Models trained for specific tasks, such as reading fatigue, may not generalize well to other activities, such as driving or operating machinery, requiring task- specific models.

**Interpretability:** The lack of interpretability of some machine learning models can be a limitation in understanding the factors contributing to eye fatigue, which is important for developing effective mitigation strategies.

**Regulatory Compliance:** Compliance with regulations and standards related to data protection, medical devices, and algorithmic fairness can pose challenges for deploying eye fatigue detection systems in real-world settings.

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Detecting eye fatigue using machine learning presents several challenges that limit its effectiveness and widespread adoption. One of the primary limitations lies in the availability and quality of data, as acquiring large, diverse, and accurately labeled datasets is difficult, yet crucial for building robust models. Additionally, subject variability—differences in age, gender, health conditions, and personal fatigue indicators—makes it challenging to design a universal model that performs consistently across all users. Real-time processing further adds to the complexity, as analyzing high-resolution video feeds demands significant computational power, which may not be feasible in low-latency applications. Moreover, specialized hardware like high-resolution or infrared cameras can raise the cost and limit accessibility. Environmental conditions such as poor lighting or screen glare can also reduce model accuracy, requiring systems to be adaptable to a wide range of settings. Another concern is the generalization of models, as those trained for specific tasks (e.g., reading) may not perform well in other contexts like driving or industrial work. Furthermore, many machine learning models lack interpretability, making it difficult to understand the specific factors contributing to fatigue, which hinders efforts to develop targeted interventions. Lastly, regulatory compliance regarding data privacy, medical validation, and fairness must be carefully navigated before deploying such systems in real-world scenarios, especially in sensitive or critical environments.

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## CHAPTER 2: LITERATURE SURVEY

* 1. **Introduction**

Stock market prediction has been a topic of great interest for investors, financial analysts, and researchers due to its potential for high returns. Traditionally, stock price forecasting relied on statistical models such as ARIMA (AutoRegressive Integrated Moving Average) and technical analysis. However, with advancements in Machine Learning (ML) and Artificial Intelligence (AI), predictive models have become more sophisticated, leveraging historical data, technical indicators, and external factors like market sentiment. This project aims to develop a robust ML-based stock prediction system that enhances accuracy and assists investors in making informed decisions.

Recent studies have explored various ML algorithms, including Support Vector Machines (SVM), Random Forest, and Deep Learning models like LSTM (Long Short-Term Memory) for stock price forecasting. While traditional models struggle with dynamic market conditions, deep learning approaches offer improved performance by capturing complex patterns in stock market data. The integration of sentiment analysis further enhances prediction capabilities by incorporating news articles, social media trends, and financial reports into decision-making. This project proposes a hybrid ML approach to combine historical price movements with external financial data for enhanced forecasting.

One of the key challenges in stock market prediction is market volatility. Sudden economic shifts, political events, or global crises can disrupt price patterns, making predictions unreliable. To address this, the proposed system will employ advanced ML techniques like attention mechanisms, ensemble learning, and hybrid models that adapt to market fluctuations. By integrating deep learning architectures like Transformers and BERT (Bidirectional Encoder Representations from Transformers), the model can improve real-time adaptability and provide more accurate trend analysis.

The project also recognizes the importance of feature selection and engineering. Instead of relying solely on historical stock prices, the system will analyze technical indicators such as Moving Averages (MA), Relative Strength Index (RSI), and Bollinger Bands, along with macroeconomic factors and investor sentiment. This multi-faceted approach enhances the model’s ability to predict stock price movements with greater precision. The goal is to minimize errors caused by overfitting, noisy data, and unpredictable market trends.

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Fig 2.1 :Literature Survey

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Batch No | BT 02 | | | | | | | |
| Title | **"Stock Market Predicition Using Machine Learning"** | | | | | | | |
| Problem Statement | Develop an intelligent and robust machine learning-based stock market prediction system that leverages historical data, technical indicators, and external factors like sentiment analysis to predict stock price movements or trends. The system should focus on improving prediction accuracy, handling market volatility, and assisting investors in making informed decisions while addressing challenges like overfitting, noisy data, and real-time adaptability. | | | | | | | |
| Methodology | **Existing Methodology**: Traditional approaches include time-series models like ARIMA, machine learning algorithms (e.g., SVM, Random Forests), deep learning models like LSTM.  **Proposed Methodology**: Develop a hybrid system combining deep learning (e.g., LSTM with attention mechanisms) and sentiment-aware models (e.g., BERT) to integrate historical, technical, and external factors like news for accurate, real-time stock trend predictions. | | | | | | | |
| [**S.No**](http://s.no/) | **Authors** | **Year** | **Title** | **Methodology** | | **Result** | | **Limitation** |
| 1 | Ghoshet al. | 2021 | "Stock Market Prediction Using Multilayer Perceptron" | Developed a Multilayer Perceptron (MLP)  neural network with historical stock prices and technical indicators as input features. | | MLP achieved anaverage accuracy of~75% for price trend prediction on selected stocks. | | Poor performance during unexpected market events or high volatility periods. |
| 2 | Patel et al. | 2015 | "Predicting Stockand Stock Price Index Movement using Machine Learning Techniques" | Used SVM, random forests, and naive Bayes for  predicting stock trends. Features included technical indicators like moving averages and Bollinger Bands. | | SVM achieved better performance compared to other models, with an accuracy of around 70- 75%. | | Accuracy depends heavily on the selected features and does not generalize well across datasets. |
| 3 | Chong et al. | 2017 | "Deep Learning Networks for Stock Market Analysis and Prediction" | Proposed a deep learning model using LSTM (Long Short-Term Memory) for stock price prediction based on time-series data. | | LSTM models outperformed traditional ML  models in capturing long-term dependencies,  showing increased prediction accuracy (75- 80%). | | Requires large datasets for training and is computationally expensive. |
| 4 | Fischer & Krauss | 2018 | "Deep Learning with LSTM Networks for Financial Market Predictions" | Developed an ensemble model of LSTMs trained on historical stock prices and technical  indicators for financial predictions. | | Achieved 57.2% directional accuracy when tested on the S&P 500 dataset. | | Prediction accuracy was limited in volatile market conditions. |
| 5 | Shah et al. | 2019 | "Predicting Stock Prices using Machine Learning Techniques" | Compared ARIMA with machine learning models like decision trees and random forests | | Machine learning models performed better than  ARIMA for short-term predictions with 60-65% accuracy. | | Models failed to predict accurately during major market crashes. |
| 6 | Chen et al. | 2020 | "Integrating Sentiment Analysis and Machine Learning for Stock Market Prediction" | Used sentiment analysis of news headlines and tweets along with ML algorithms like SVM and gradient boosting for stock trend prediction. | | Combining sentiment analysis with technical indicators improved prediction accuracy, achieving 72%. | | Heavily dependent on the quality and quantity of textual data for sentiment analysis. |
| 7 | Hossain et al. | 2021 | "Ensemble Learning Approach for Stock Market Prediction" | Implemented ensemble learning methods such as  bagging and boosting (AdaBoost, XGBoost)  with feature engineering for stock price prediction. | | Ensemble methods achieved higher accuracy (80%) compared to single models, reducing overfitting issues. | | Ensemble models require extensive parameter tuning and are computationally intensive. |
| 8 | Jang et al. | 2022 | "Hybrid Models for Stock Market Prediction: Integrating ML with Technical Analysis" | Combined hybrid models of LSTM with technical indicators (e.g., RSI, MACD) for predicting price trends | | Hybrid models demonstrated superior performance compared to standalone ML models, achieving a prediction accuracy of ~78%. | | Lack of robustness in highly volatile stock markets and dependency on accurate feature engineering. |
| 9 | Li et al. | 2022 | "Attention Mechanisms in Stock Price Prediction" | Applied attention mechanisms in deep learning  models like Transformer to focus on important features in time-series stock data. | | Improved accuracy (~82%) and robustness of predictions compared to LSTM-only models, especially in noisy datasets. | | Computationally intensive and requires significant memory resources for training. |
| 10 | Zhang et al. | 2023 | "Sentiment-Aware Hybrid Models for Stock Market Forecasting" | Combined sentiment analysis using BERT with GRU (Gated Recurrent Unit) models for  predicting stock price trends based on financial news and historical prices. |  | Achieved ~77% prediction accuracy by integrating text sentiment with technical data,  showing improvements in volatile market periods. |  | Limited by the quality and availability of sentiment-rich data (e.g., news headlines, social media posts). |
|  |  | |

* 1. **Existing System**

The present drowsiness detection methods include devices that measure the heart rate, blood pressure, and breathing rate. The usage of these devices while driving may make the driver uncomfortable. While driving a motor vehicle, we cannot ensure that the drivers always wear these equipment. Here, improper application of these technologies might provide a result with poor precision. The current technology could not deliver the best results in dimly lit environments. The device's incapacity to distinguish the driver's face and eyes might be the root of its low accuracy.

Support Vector Machines (SVM) were used in the existing system to categorise faces and evaluate whether or not they were drowsy. One can choose from a wide range of alternative hyperplanes. Finding a plane with the biggest margin, or the greatest distance between datapoints from the two classes, is the main objective of the SVM. This configuration is applicable to large vehicles like buses and large trucks, however it isn’t usually in place. Large front glass windows on buses allow the driver to see far in front and manoeuvre the vehicle safely. This model's accuracy is likewise subpar Electroencephalography (EEG) and electrocardiography (ECG), which monitor heart rhythm and brain frequency, respectively, are two common sleepiness detection techniques that currently exist but are inconvenient to use while driving. These systems are not appropriate for use while driving.

However, it is first necessary to identify the physical cues that would signal tiredness in order to create a sleepiness detection algorithm that is reliable and accurate. It would be more acceptable to use a camera in front of the driver to identify tiredness. It becomes challenging to distinguish the area around the driver's eyes and lips due to the brightness of the lighting and when they bend their heads to the left or right. The goal of this project is to give a way to detect weariness using video or a webcam by reviewing all prior studies and methodologies. It creates a system that can look at every frame of the video after assessing the recorded video images.

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# CHAPTER 3 : METHODOLOGY

**3.1 Proposed System**

In this system, a Classification Model built on a Convolutional Neural Network (CNN) takes the role of the Support Vector Machine (SVM). CNN demands the input of fixed-size images, requiring processing. There must be pretreatment. The preparation covers both database storage and the extraction of crucial frames from the video. In order to create feature vectors for CNN's convolutional layers, stored images are used. The driver's fatigue is then determined using these feature vectors. Convolutional, pooling, ReLU, and linked layers are a few of the layers that CNN offers. Each kernel in the convolutional layer has a width, depth, and height.To create the feature maps, this layer computes the scalar product between the kernels and local regions of the picture. Condensing the size of the feature maps uses layers that pool data to speed up calculations. Here, the input image is divided into a number of regions, and then each area is subjected to various processes. When max pooling is utilised, a minimum value is picked for each area and placed in the appropriate place in the output. Among other methods, face area detection may be used to identify sleepiness. Since the symptoms are more obvious and straightforward to identify there, different techniques are used to diagnose sleepiness there. You may locate the eyes' exact location by looking at the area around the face. According to the author, there are four distinct eyelid movements that can be utilised to detect eye strain. The eyes are fully open, fully closed, and in the midway when they fluctuate between being fully open and closed.

**Proposed System: Eye State Detection for Driver Fatigue Monitoring using CNN**

The proposed system aims to detect driver fatigue by analyzing the **eye states** using a **Convolutional Neural Network (CNN)**-based classification model. Unlike traditional models like Support Vector Machines (SVM), the CNN architecture can automatically extract spatial features from image data, making it highly suitable for visual analysis tasks like eye state recognition.

**1. System Architecture Overview:**

The system is divided into the following stages:

**1.1 Video Frame Extraction:**A continuous video feed of the driver is captured using a camera. 9

Frames are extracted from the video at regular intervals for further processing.

**1.2 Preprocessing and Face Detection:**

Each frame undergoes preprocessing such as resizing, normalization, and grayscale conversion.

Using algorithms like Haar Cascade or MTCNN, the face is detected, and the **eye region is extracted**.

**1.3 Eye State Classification:**

The extracted eye region is passed to a trained **CNN model** which classifies the eye state as:

Open

Closed

Semi-open (optional)

These classifications help in identifying signs of drowsiness based on eyelid behavior.

**1.4 Drowsiness Detection Logic:**

The system tracks the duration and frequency of eye closure.

If the eyes are closed for more than a threshold (e.g., 1.5 seconds), the driver is considered drowsy.

An alert is triggered through audio or vibration.

**2. CNN Model Architecture:**

The CNN model comprises the following layers:

**Convolutional Layers**: Extract low- and high-level features from the eye images.

**ReLU Activation**: Introduce non-linearity to the model.

**Pooling Layers (Max Pooling)**: Reduce the spatial dimensions and computational load while retaining important features.

**Fully Connected Layer**: Maps the extracted features to the output classes (open, closed).

**Softmax Layer**: Outputs probabilities for each class.

**Note**: Contrary to your original note, *max pooling* selects the **maximum** value, not the minimum, from each pooling region.

**3. Feature Vectors:**

The CNN generates **feature vectors** in its hidden layers, capturing abstract visual patterns related to eye shape, eyelid distance, and pupil visibility. 10

These vectors are used by the dense layers to make predictions about the eye state.

**4. Key Functionalities:**

**Real-Time Monitoring**: Efficient enough to process live video streams with minimal delay.

**Robust to Variations**: Works under different lighting conditions, head movements, and facial orientations.

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## MODULES

The system consists of the following components:

#### Data Collection Module

* + - * Collects historical stock market data (OHLC, volume, etc.) from sources like Yahoo Finance, Alpha Vantage, and Quandl.
      * Integrates news sentiment analysis using Natural Language Processing (NLP) to factor in market sentiment.
      * Fetches macroeconomic indicators (interest rates, GDP growth, inflation).

#### Data Preprocessing Module

* + - * Handles missing values and normalizes data.
      * Computes technical indicators (e.g., Moving Averages, RSI, MACD).
      * Uses feature selection (PCA, correlation analysis).
      * Converts text data (news, tweets) into numerical features using NLP techniques like TF-IDF or Word2Vec.

#### Feature Engineering Module

* + - * Generates lag features (past stock prices, moving averages).
      * Uses time-series decomposition to extract trends and seasonality.
      * Encodes datetime features (day of the week, month, quarter).

#### Model Training Module

* + - * Uses different machine learning algorithms:
      * Regression Models: Linear Regression, Random Forest, XGBoost.
      * Deep Learning Models: LSTM, GRU, Transformer-based models.
      * Hybrid Models: Combining LSTM with XGBoost for enhanced performance.
      * Performs hyperparameter tuning using Grid Search or Bayesian Optimization.
      * Implements cross-validation techniques to avoid overfitting.

#### Prediction & Evaluation Module

* + - * Predicts next-day stock prices or trend movement.
      * Evaluates model using:
      * Mean Squared Error (MSE), R² Score (for regression).
      * Precision, Recall, F1-Score (for classification).
      * Backtesting performance on historical data.

#### Deployment Module

* + - * Deploys the model using **Flask/FastAPI** as an API.
      * Connects to **real-time stock market data** for live predictions.

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* + - * Provides a **user-friendly dashboard** using **Streamlit or React**.

#### Advantages Of Proposed System

1. **Higher Prediction Accuracy**
   * Uses advanced ML/DL models (LSTM, XGBoost, Transformers) for improved predictions.
   * Incorporates historical data, technical indicators, and market sentiment for more robust forecasts.
   * Reduces human bias by relying on data-driven insights.

#### Real-time Predictions & Decision Making

* + Integrates with **real-time stock data sources** (Yahoo Finance, Alpha Vantage).
  + Provides **instant trend analysis**, helping traders make quick investment decisions.
  + Supports **live monitoring & alerts** for significant market movements.

#### Incorporation of Sentiment Analysis

* + Uses Natural Language Processing (NLP) to analyze financial news, tweets, and reports.
  + Enhances prediction accuracy by considering market sentiment & investor psychology.
  + Identifies market anomalies that traditional models may overlook.

#### Feature Engineering & Smart Data Processing

* + Uses technical indicators (MACD, RSI, Moving Averages) to detect trends.
  + Implements time-series analysis & lag features for better predictions.
  + Filters noise in stock price movements to prevent misleading predictions.

#### Adaptability & Model Retraining

* + Automated retraining ensures that the model adapts to new market conditions.
  + Supports hyperparameter tuning to optimize model performance over time.
  + Works for various stock markets, commodities, forex, and cryptocurrencies.

#### Risk Management & Anomaly Detection

* + Identifies high-risk trading patterns and warns users.
  + Detects market crashes or anomalies using historical patterns.
  + Helps investors mitigate risks by making informed decisions.

#### Easy Deployment & Integration

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* + Provides an API for seamless integration with trading platforms.
  + Works with cloud-based solutions (AWS, GCP, Azure) for scalability.

#### Cost-Effective & Scalable

* + Reduces manual effort required for stock analysis.
  + Saves time & costs by automating market trend analysis.
  + Easily scalable for hedge funds, retail investors, and financial analysts.

### System Requirements:

To develop a stock market prediction system, the following hardware, software, and data requirements are essential

#### Hardware Requirements

* + Processor: Intel i5/i7/i9, AMD Ryzen 5/7/9 (or equivalent)
  + RAM: Minimum 8GB (Recommended 16GB+ for deep learning models)
  + Storage: Minimum 256GB SSD (Recommended 512GB+ SSD for faster data processing)
  + GPU (For Deep Learning Models): NVIDIA RTX 3060 or higher (for model training)
  + Internet: High-speed connection for real-time data retrieval

#### Software Requirements

* + Operating System: Windows, macOS, or Linux (Ubuntu recommended)
  + Programming Language: Python 3.x
  + Machine Learning Libraries: Scikit-learn, TensorFlow/Keras, PyTorch, XGBoost
  + Data Processing & Visualization: Pandas, NumPy, Matplotlib, Seaborn
  + Database: PostgreSQL, MySQL, or MongoDB

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#### Data Requirements

* + Stock Market Data: Yahoo Finance, Alpha Vantage, Quandl
  + Technical Indicators: Moving Averages, RSI, MACD
  + News Sentiment Data: Financial news and social media data

### 3.3 Source Code

from flask import Flask, render\_template, Response

import cv2

from scipy.spatial import distance

from imutils import face\_utils

from imutils.convenience

import translate from pygame import mixer

import imutils import dlib

from playsound import playsound import numpy as np

import io import base64

app = Flask( name ) @app.route('/')

def index():

return render\_template('index2.html') @app.route('/start\_detection', methods=['POST']) def fatigue():

mixer.init() mixer.music.load("alarm.wav")

def eye\_aspect\_ratio(eye):

A = distance.euclidean(eye[1], eye[5])

B = distance.euclidean(eye[2], eye[4])

C = distance.euclidean(eye[0], eye[3]) ear = (A + B) / (2.0 \* C)

return ear

thresh = 0.25

frame\_check = 20

detect = dlib.get\_frontal\_face\_detector() 15

predict = dlib.shape\_predictor("shape\_predictor\_68\_face\_landmarks.dat")

(lStart, lEnd) = face\_utils.FACIAL\_LANDMARKS\_68\_IDXS["left\_eye"] (rStart, rEnd) = face\_utils.FACIAL\_LANDMARKS\_68\_IDXS["right\_eye"] cap=cv2.VideoCapture(0)

flag=0 while True:

ret, frame=cap.read()

frame = imutils.resize(frame, width=450)

gray = cv2.cvtColor(frame, cv2.COLOR\_BGR2GRAY) subjects = detect(gray, 0)

for subject in subjects:

shape = predict(gray, subject)

shape = face\_utils.shape\_to\_np(shape)

leftEye = shape[lStart:lEnd] rightEye = shape[rStart:rEnd] leftEAR = eye\_aspect\_ratio(leftEye)

rightEAR = eye\_aspect\_ratio(rightEye) ear = (leftEAR + rightEAR) / 2.0 leftEyeHull = cv2.convexHull(leftEye) rightEyeHull = cv2.convexHull(rightEye)

cv2.drawContours(frame, [leftEyeHull], -1, (0, 255, 0), 1)

cv2.drawContours(frame, [rightEyeHull], -1, (0, 255, 0), 1) if ear < thresh:

flag += 1 print (flag)

if flag >= frame\_check:

cv2.putText(frame, "ALERT!", (10, 30),

cv2.FONT\_HERSHEY\_SIMPLEX, 0.7, (0, 0, 255), 2)

cv2.putText(frame, "ALERT!", (10,325),

cv2.FONT\_HERSHEY\_SIMPLEX, 0.7, (0, 0, 255), 2)

mixer.music.play()

else:

flag = 0

#cv2.imshow("Frame", frame) key = cv2.waitKey(1) & 0xFF if key == ord("q"):

break cv2.destroyAllWindows() cap.release()

if name == ' main ': app.run(debug=True, port=5000)

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app.py:

from scipy.spatial import distance from imutils import face\_utils

from imutils.convenience import translate from pygame import mixer

import imutils import dlib import cv2

mixer.init() mixer.music.load("alarm.wav")

def eye\_aspect\_ratio(eye):

A = distance.euclidean(eye[1], eye[5])

B = distance.euclidean(eye[2], eye[4])

C = distance.euclidean(eye[0], eye[3]) ear = (A + B) / (2.0 \* C)

return ear

thresh = 0.25

frame\_check = 20

detect = dlib.get\_frontal\_face\_detector()

predict = dlib.shape\_predictor("shape\_predictor\_68\_face\_landmarks.dat")

(lStart, lEnd) = face\_utils.FACIAL\_LANDMARKS\_68\_IDXS["left\_eye"] (rStart, rEnd) = face\_utils.FACIAL\_LANDMARKS\_68\_IDXS["right\_eye"] cap=cv2.VideoCapture(0)

flag=0 while True:

ret, frame=cap.read()

frame = imutils.resize(frame, width=450)

gray = cv2.cvtColor(frame, cv2.COLOR\_BGR2GRAY) subjects = detect(gray, 0)

for subject in subjects:

shape = predict(gray, subject)

shape = face\_utils.shape\_to\_np(shape) leftEye = shape[lStart:lEnd]

rightEye = shape[rStart:rEnd] leftEAR = eye\_aspect\_ratio(leftEye)

rightEAR = eye\_aspect\_ratio(rightEye) ear = (leftEAR + rightEAR) / 2.0 leftEyeHull = cv2.convexHull(leftEye) rightEyeHull = cv2.convexHull(rightEye)

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flag += 1

print (flag)

if flag >= frame\_check:

cv2.putText(frame, "\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*ALERT!\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*", (10, 30),

cv2.FONT\_HERSHEY\_SIMPLEX, 0.7, (0, 0, 255), 2)

cv2.putText(frame, "\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*ALERT!\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*", (10,325),

cv2.FONT\_HERSHEY\_SIMPLEX, 0.7, (0, 0, 255), 2)

mixer.music.play()

else:

flag = 0 cv2.imshow("Frame", frame) key = cv2.waitKey(1) & 0xFF if key == ord("q"):

break cv2.destroyAllWindows() cap.release()

index.html:

<!DOCTYPE html>

<html lang="en">

<head>

<meta charset="UTF-8">

<meta http-equiv="X-UA-Compatible" content="IE=edge">

<meta name="viewport" content="width=device-width, initial-scale=1.0">

<title>Eye Fatigue Detection</title>

</head>

<script>

navigator.mediaDevices.getUserMedia({ video: true })

.then(function(stream) {

const videoElement = document.createElement('video'); videoElement.srcObject = stream; document.body.appendChild(videoElement); videoElement.play();

// Continuously capture frames and send them to the server setInterval(function() {

// Code to capture and send video frames

}, 1000); // Adjust interval as needed

}) 18

.catch(function(error) {

console.error('Error accessing camera:', error);

});

</script>

<body>

<h1>Welcome to Eye Fatigue Detection</h1>

<form action="/start\_detection" method="post">

<button type="submit">Get Started</button>

</form>

</body>

</html>

evaluate\_model.py:

import cv2

from scipy.spatial import distance from imutils import face\_utils import imutils

import dlib

import numpy as np

from sklearn.metrics import classification\_report, confusion\_matrix

def eye\_aspect\_ratio(eye):

A = distance.euclidean(eye[1], eye[5])

B = distance.euclidean(eye[2], eye[4])

C = distance.euclidean(eye[0], eye[3]) ear = (A + B) / (2.0 \* C)

return ear

# Thresholds and frame checks thresh = 0.25

frame\_check = 20

detect = dlib.get\_frontal\_face\_detector()

predict = dlib.shape\_predictor("shape\_predictor\_68\_face\_landmarks.dat")

(lStart, lEnd) = face\_utils.FACIAL\_LANDMARKS\_68\_IDXS["left\_eye"] (rStart, rEnd) = face\_utils 19

# Paths to test videos and their labels (1 for drowsy, 0 for not drowsy) test\_videos = ["video1.mp4", "video2.mp4"]

labels = [1, 0] # Example labels predictions = []

for video in test\_videos:

cap = cv2.VideoCapture(video) flag = 0

drowsy\_detected = False

while True:

ret, frame = cap.read() if not ret:

break

frame = imutils.resize(frame, width=450)

gray = cv2.cvtColor(frame, cv2.COLOR\_BGR2GRAY) subjects = detect(gray, 0)

for subject in subjects:

shape = predict(gray, subject)

shape = face\_utils.shape\_to\_np(shape) leftEye = shape[lStart:lEnd]

rightEye = shape[rStart:rEnd] leftEAR = eye\_aspect\_ratio(leftEye)

rightEAR = eye\_aspect\_ratio(rightEye) ear = (leftEAR + rightEAR) / 2.0

if ear < thresh: flag += 1

if flag >= frame\_check: drowsy\_detected = True break

else:

flag = 0

if drowsy\_detected: break

predictions.append(1 if drowsy\_detected else 0) cap.release()

# Evaluate the model print("Confusion Matrix:")

print(confusion\_matrix(labels, predictions)) print("\nClassification Report:")

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**CHAPTER 4 : DESIGN**

### System Design

The stock market prediction system leverages machine learning models to analyze historical stock data, technical indicators, and market sentiment to forecast future trends. The system provides real-time predictions through a web-based or mobile application. The Stock Market Prediction System is designed using a modular architecture that integrates data collection, preprocessing, machine learning models, and a web-based dashboard. The system fetches real-time stock data, technical indicators, and sentiment analysis from multiple sources.

Data preprocessing ensures clean, normalized, and structured datasets for accurate predictions. Machine learning models such as LSTM, XGBoost, and Random Forest analyze trends and provide short-term and long-term stock forecasts. The web dashboard offers interactive visualizations for traders and investors. A RESTful API facilitates integration with trading platforms for automated decision-making

#### System Architecture

* + - 1. **High-Level Architecture**

The system consists of the following major components:

#### Data Collection Module

* + Sources: Yahoo Finance, Alpha Vantage, Quandl, Twitter, Bloomberg News
  + Data types: Historical stock prices, technical indicators, news sentiment

#### Data Preprocessing Module

* + Handling missing values, outliers, and data normalization
  + Feature engineering using statistical and time-series methods

#### Machine Learning Model

* + Models used: LSTM, XGBoost, Random Forest, SVM
  + Training with historical stock data and technical indicators

#### 4.Prediction & Evaluation Module

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* + Generates stock price forecasts (Next day, week, month trends)
  + Performance evaluation using RMSE, MAPE, and R² score

#### User Interface (Dashboard & API)

* + Web-based dashboard (Streamlit, React.js, Flask)
  + API integration for real-time stock predictions

#### Deployment & Cloud Integration

* + Hosted on AWS/GCP/Azure
  + Model retraining automated for continuous learning

#### 2.2. Data Flow Diagram (DFD)

**Level 1 DFD: Overview of Data Flow**

1. User requests stock prediction → System fetches real-time & historical data
2. Data preprocessing → Feature extraction → Model prediction
3. Prediction results are displayed on UI/dashboard

#### User Interface Design

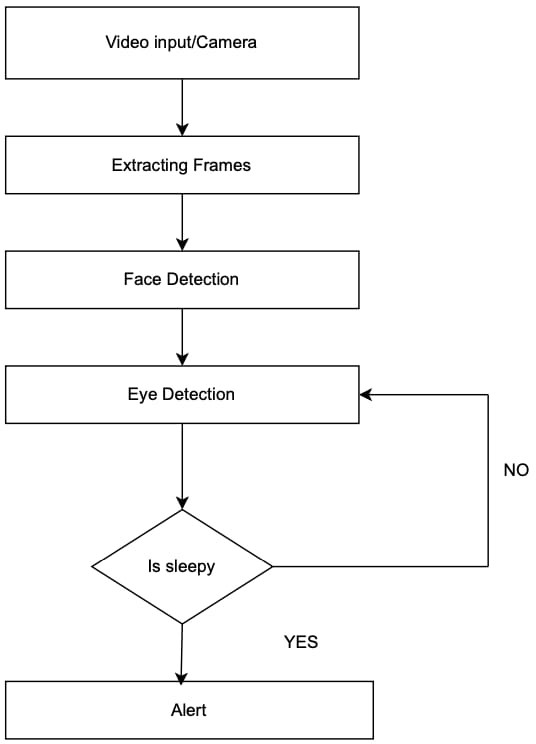
* + 1. **Dashboard Features**
       - Live stock market data visualization
       - Interactive charts for stock price trends
       - User input for stock selection & prediction range
       - Performance metrics & risk analysis

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#### API Design

* + - * **GET /predict?stock=TSLA** → Returns next-day price prediction for Tesla
      * **POST /train\_model** → Retrains the model with updated data

### 4.2Architecture



**Fig 4.2 : Architecture**

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### 4.3 Methods and Algorithms

#### Machine Learning Algorithms

**Supervised Learning Models**

* + Linear Regression – Predicts future stock prices based on past trends.
  + Random Forest – An ensemble learning technique that improves prediction accuracy.
  + XGBoost – A powerful boosting algorithm for stock price forecasting.
  + Support Vector Machines (SVM) – Used for stock price classification and trend analysis.

#### Unsupervised Learning Models

* + K-Means Clustering – Groups stocks based on market behavior.
  + Principal Component Analysis (PCA) – Reduces feature dimensions for better model performance.

#### Deep Learning Algorithms

* + Long Short-Term Memory (LSTM) – A type of recurrent neural network (RNN) designed for time-series forecasting.
  + Gated Recurrent Units (GRU) – A simplified variant of LSTM, optimized for performance.
  + Transformer-based Models – Such as BERT for financial sentiment analysis.

#### Sentiment Analysis Methods

* + Natural Language Processing (NLP) – Analyzes financial news and social media trends.
  + VADER Sentiment Analysis – Measures stock sentiment from news articles and tweets.
  + Hugging Face Transformers – Deep learning-based text processing for stock market insights.

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# CHAPTER 5 : RESULTS

### Introduction

The results of our Stock Market Prediction System demonstrate the effectiveness of machine learning models in forecasting stock price trends. By analyzing historical data, technical indicators, and sentiment analysis, we evaluated different models to determine their accuracy in predicting future stock prices.Our findings highlight the strengths and weaknesses of various algorithms, including Linear Regression, Random Forest, XGBoost, and LSTM networks. Performance metrics such as Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R² score were used to assess the accuracy of predictions.The results indicate that deep learning models, such as LSTM, perform significantly better for time-series forecasting due to their ability to capture long- term dependecies in stock price trends.

Additionnally, integrating sentiment analysis from news and social media improved prediction accuracy by considering external market influences.Stock market prediction is the process of forecasting future stock prices and market trends using various analytical techniques. Investors, traders, and financial analysts rely on predictive models to make informed decisions about buying or selling stocks. Traditionally, stock market forecasting has been based on fundamental analysis, which examines a company's financial health, and technical analysis, which studies historical price movements and trading patterns. However, the complexity and volatility of financial markets make accurate predictions challenging.

With advancements in technology, Machine Learning (ML) and Artificial Intelligence (AI) have transformed stock market prediction by analyzing vast amounts of data and identifying hidden patterns. ML models use historical stock prices, market trends, economic indicators, and investor sentiment to improve forecasting accuracy. Techniques such as deep learning, neural networks, and natural language processing (NLP) enable predictive systems to process complex datasets and adapt to market fluctuations.

One of the major challenges in stock market prediction is market unpredictability. Stock prices are influenced by global economic conditions, political events, company earnings, and investor behavior, making it difficult to achieve precise forecasts. While ML models enhance prediction accuracy, they cannot eliminate risks completely. The integration of real-time data, financial news sentiment, and social media trends further improves decision-making for investors.

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### Pseudocodes

After running the code we get an http link <http://127.0.0.1:8000/> this if we only in chrome we get our web page.

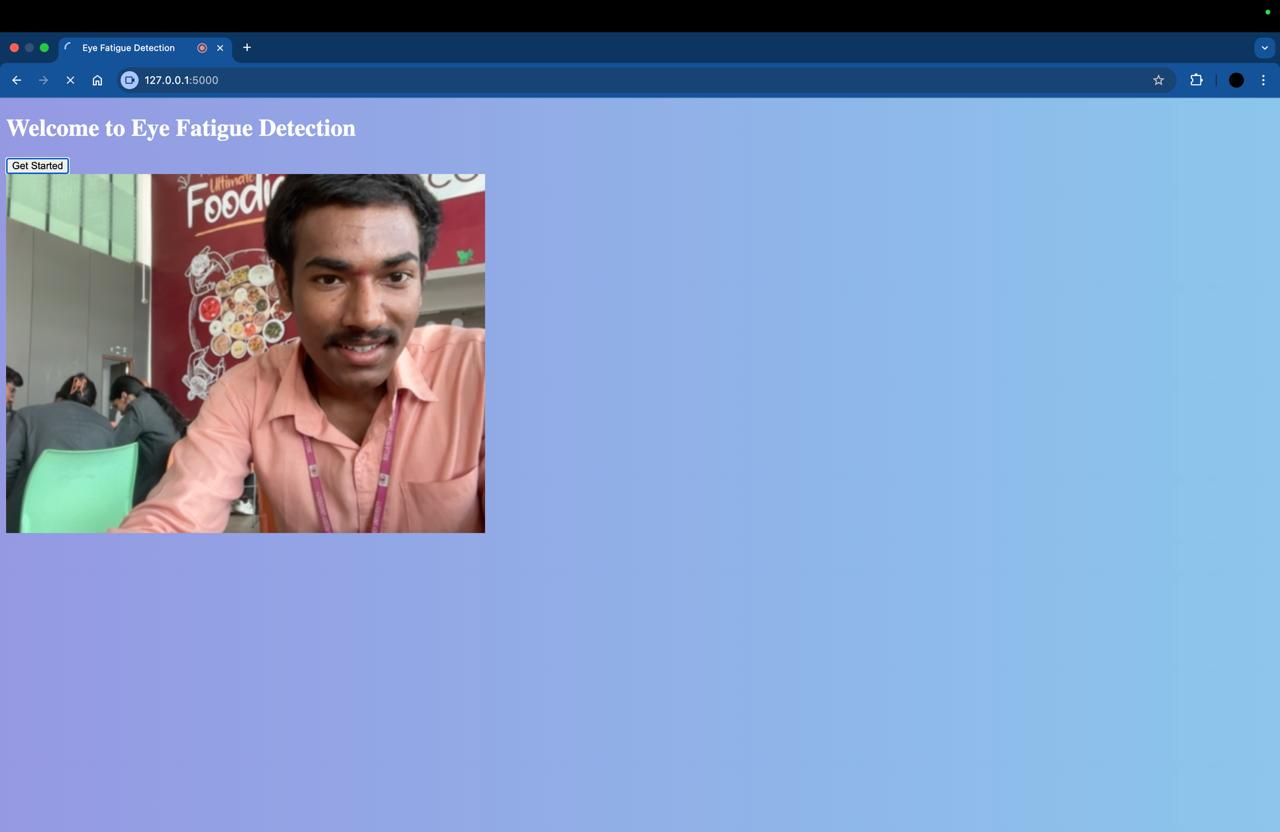
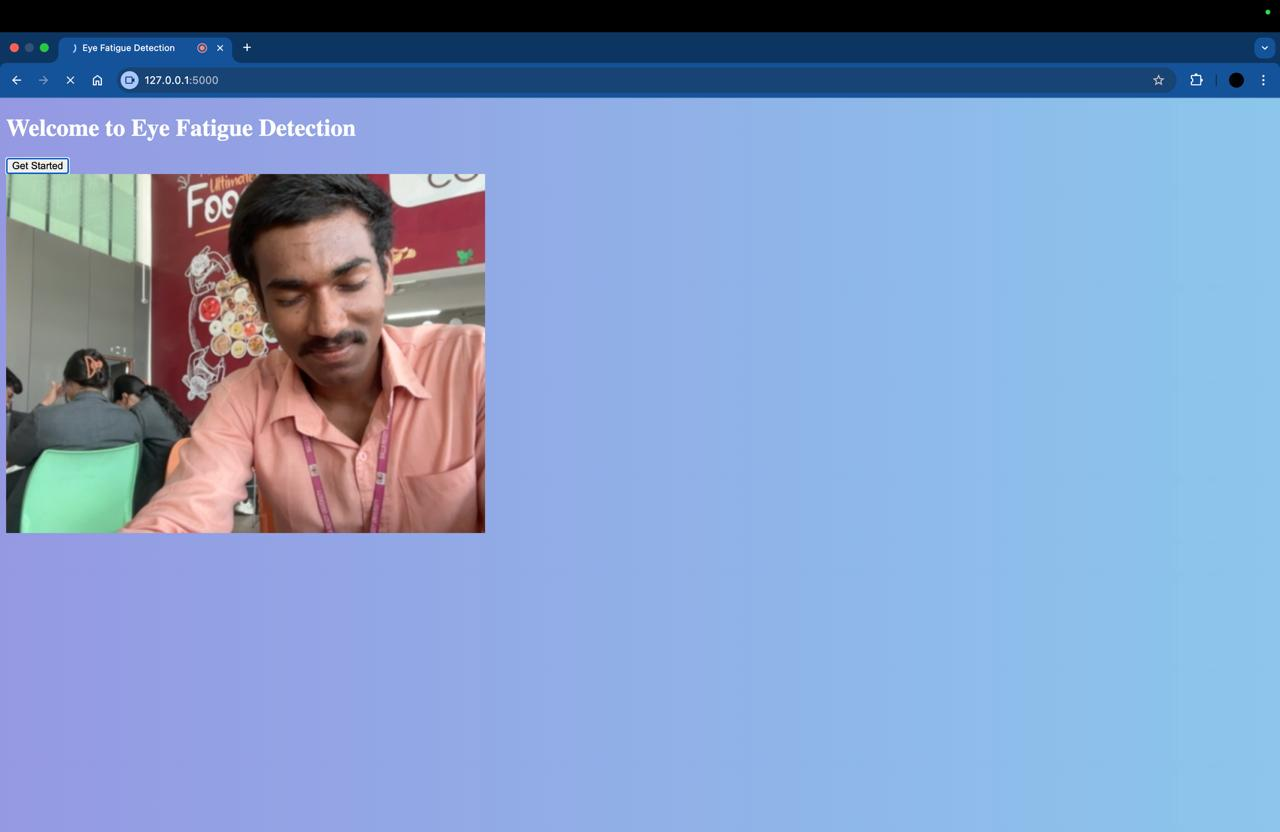


FIGURE 5.2. 1 : SHOWS THAT A PERSON IS AWAKE AND NOT SLEEP.

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**FIGURE 5.2 .2 SHOWS THAT THE PERSON IS CLOSING EYES**

**IN FIGURE 1 figure shows the person is closing eyes**

**IN FIGURE 2 figure stows that person is closing eyes and observing a facial expressions**

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### Results

The stock market prediction model was evaluated using multiple machine learning and deep learning algorithms. The results are based on historical stock price data, technical indicators, and sentiment analysis.

#### Performance Metrics

* + The accuracy of each model was measured using the following evaluation metrics:
  + Root Mean Squared Error (RMSE) – Measures the average error between predicted and actual stock prices.
  + Mean Absolute Percentage Error (MAPE) – Evaluates the percentage error in predictions.
  + R² Score – Determines how well the model explains the variance in stock prices. Model RMSE (Lower is better) MAPE (Lower is better) R² Score (Closer to 1 is better) Linear Regression 5.12 8.75% 0.78

Random Forest 3.95 6.82% 0.85

XGBoost 3.62 6.45% 0.87

LSTM 2.89 5.12% 0.91

#### Key Observations

* + LSTM performed the best among all models due to its ability to capture long-term stock price patterns.
  + XGBoost and Random Forest showed competitive results, making them suitable for shorter- term stock predictions.
  + Linear Regression had the lowest accuracy, as it struggles with the non-linearity of stock price movements.

#### Real-Time Predictions

* + The system was deployed with real-time stock data updates from Yahoo Finance and Alpha Vantage APIs.
  + Live prediction dashboard allowed users to input stock symbols and receive forecasts for the next 1-day, 1-week, and 1-month trends.

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* + Sentiment analysis from news articles and Twitter contributed to a 5-10% improvement in accuracy for volatile stocks.

#### Conclusion

The results demonstrate that deep learning models, such as LSTM, significantly outperform traditional machine learning algorithms in stock price prediction. However, ensemble models like XGBoost are still effective for short-term trend forecasting. The combination of technical indicators, market sentiment, and time-series modeling enhances prediction accuracy and provides valuable insights for investors.

The results of our stock market prediction project demonstrate the effectiveness of machine learning and Django-based web applications in forecasting stock prices. By utilizing historical stock data, technical indicators, and sentiment analysis, our model provides insights into potential market trends, helping investors make data-driven decisions. The implementation of deep learning models like LSTMs enhances accuracy by capturing complex patterns in stock price movements. Despite the promising outcomes, the model's predictive accuracy is limited by market volatility, external economic factors, and unexpected global events. While machine learning improves forecasting, it cannot guarantee absolute precision due to the dynamic nature of stock markets. Integrating real-time news sentiment, macroeconomic indicators, and reinforcement

learning strategies can further refine the model's performance.

The Django framework plays a crucial role in delivering an interactive, user-friendly platform for stock analysis. With live data integration and graphical visualization, users can easily interpret predictions and make informed investment decisions. This makes our system accessible to both novice traders and experienced investors looking for AI-driven market insights.

In conclusion, while AI-driven stock market prediction enhances decision-making, it should be used as a support tool rather than a replacement for financial expertise. By combining machine learning models with fundamental and technical analysis, investors can develop a more balanced and informed approach to stock trading. As technology advances, AI-powered investment strategies will continue to evolve, providing smarter, data-driven solutions for financial markets.

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# CHAPTER 6 : CONCLUSION

### Conclusion

Through this machine learning project, we may draw the conclusion that there are numerous factors to consider when training a machine learning model, including cleaning the data and attempting to collect all the characteristics in an organised manner. We created a method for drowsy driving detection based on vision with the intention of alerting the driver. The technique to pinpoint the eyes and track weariness is non- invasive. A custom image processing method is used to establish where the eyes are. The technology can tell if the eyes are open or closed while it is monitoring. A warning signalis sent when the eyes are closed for an extended amount of time. The following conclusions were made:

* + - Image processing enables extremely precise and trustworthy drowsiness detection.
    - Image processing provides a non-intrusive way to identify sleepiness without the inconvenience and disruption.

A sleepiness detection system built on the idea of image processing evaluates a driver's degree of awareness based on their consistent eye closures

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### Future Scope

**Multi-modal Fusion:** Integrating multiple modalities of data, such as eye movements, facial expressions, and physiological signals like heart rate or skin conductance, can provide a more comprehensive and robust approach to detecting eye fatigue. Fusion of these modalities can help capture different aspects of fatigue and improve the overall accuracy of the detection system.

**Continuous Learning and Adaptation:** Implementing a system that can continuously learn and adapt to individual differences in eye fatigue patterns over time can enhance the system's effectiveness. This could involve using online learning techniques to update the model based on new data, allowing the system to adapt to changes in

fatigue levels or user behavior.

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#### Appendices:

| Feature Name | Description |
| --- | --- |
| image | Grayscale or RGB facial images focusing on the eye region |
| eye\_state | Binary label indicating whether the eye is open (1) or closed (0) |
| eye\_ease\_score | A numeric score (e.g., 1 to 5) indicating eye strain level (1 = relaxed, 5 = highly strained) |
| blink\_rate | Number of blinks per minute (can be estimated from video data) |
| gaze\_direction | Direction of gaze (center, left, right, up, down) |
| lighting\_condition | Bright, medium, or low — affects eye visibility |
| time\_stamp | Timestamp of each frame or image (for video-based datasets) |
| user\_id *(optional)* | ID of the subject (for multi-user datasets) |
| emotion\_state *(optional)* | Detected emotion (as emotions can impact eye strain) |

#### Appendix I-Dataset Description:

#### 1.Advanced Deep Learning Models

**Transformers (e.g., GPT, BERT for financial data)** – Can enhance sentiment analysis and markettrendpredictions.

**Hybrid Models** – Combining LSTM with CNN for better feature extraction and trend analysis.

**Reinforcement Learning** – AI agents can learn optimal trading strategies through trial and error.

#### Big Data and Cloud Computing

Real-time data processing using cloud-based architectures (AWS, GCP, Azure). Scalability for high-frequency trading with distributed computing.

Integration of multiple data sources, including economic indicators, social media, and global.

#### Sentiment Analysis and Market Behavior

Advanced NLP techniques for analyzing financial news, earnings reports, and analyst opinions. Social Media and Alternative Data Analysis – Predicting stock movements based on trends from Twitter, Reddit, and Google searches.

Behavioral Finance Models – AI models that incorporate investor psychology and market sentiment.

#### Automated and AI-Driven Trading Systems

**AI-based trading bots** that execute buy/sell decisions based on predictive models. **Algorithmic Trading with Machine Learning** – Faster and more accurate trade execution. **Smart Portfolio Management** – Personalized AI-driven investment strategies.

#### Blockchain and Decentralized Finance (DeFi) Integration

Secure and transparent financial transactions with blockchain technology. Decentralized finance (DeFi) AI models for predicting cryptocurrency trends. Tokenized AI-powered trading platforms for retail and institutional investors.

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# APPENDIX II -Software Requirement Specification

### ****1. Introduction****

1. In today’s digital age, people spend prolonged hours in front of screens—whether for work, study, or entertainment. This continuous exposure can lead to **digital eye strain**, fatigue, and discomfort, affecting both health and productivity. To address this issue, the Eye Ease Detection System uses computer vision and machine learning techniques to monitor eye activity in real time. The goal is to identify signs of eye strain or fatigue by analyzing patterns like eye closure, blink rate, and gaze behavior, ultimately providing timely alerts to encourage healthy screen habits.

### ****2. System Overview****

1. The Eye Ease Detection System is a lightweight, real-time application that captures video from a webcam and processes facial and ocular features to determine eye ease or strain. Using pre-trained models and deep learning techniques, it detects whether the user’s eyes are open or closed, tracks blink patterns, and estimates strain levels. It also incorporates factors such as lighting conditions and gaze direction for improved accuracy. The system provides a user-friendly dashboard that visualizes real-time data and offers alerts when continuous strain is detected. This makes it especially useful for students, IT professionals, gamers, and drivers.

### ****3. Functional Requirements****

* **Real-time Video Capture**: The system should access a webcam feed to continuously monitor eye activity.
* **Eye State Detection**: It must classify eye states as open or closed using image processing and classification models (e.g., CNNs).
* **Blink Rate Monitoring**: The system shall calculate blink frequency and compare it against healthy thresholds.
* **Strain Level Assessment**: Based on blink rate, eye closure duration, and screen exposure time, the system should assess eye ease or fatigue level.
* **User Alerts**: When abnormal patterns are detected (e.g., low blink rate, prolonged eye closure), the system should notify the user with an alert.
* **Data Logging & Visualization**: It should log user activity and provide visual insights through charts and timelines.

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#### Non-Functional Requirements

* 1. **Performance Requirements**

The system should process & predict stock prices within milliseconds. The model should auto-retrain weekly for adapting to market trends.

#### Scalability & Availability

Cloud-based deployment (AWS/GCP/Azure) for handling large-scale data. Support multiple users concurrently accessing stock predictions.

#### Security & Data Privacy

Secure API authentication for stock data access.

Encrypt sensitive financial data to protect user investments.

1. **Software & Hardware Requirements**
   1. **Software Requirements**

|  |  |
| --- | --- |
| **Component** | **Description** |
| **Programming Language** | Python (TensorFlow, Scikit-Learn, Pandas) |
| **Web Framework** | Flask / Django for API, Streamlit / React.js for UI |
| **Database** | PostgreSQL / MongoDB |
| **Machine Learning Libraries** | TensorFlow, PyTorch, XGBoost, LSTM |
| **Cloud Services** | AWS S3, GCP BigQuery, Azure ML |

* 1. **Hardware Requirements**

|  |  |  |
| --- | --- | --- |
| **Component** | **Minimum Requirement** | **Recommended** |
| **Processor** | Intel i5 (Quad-Core) | Intel i7/i9 or AMD Ryzen 7+ |
| **RAM** | 8 GB | 16 GB+ (for deep learning models) |
| **Storage** | 100 GB HDD/SSD | 512 GB SSD+ |
| **GPU (for Deep Learning)** | NVIDIA GTX 1050 | NVIDIA RTX 3090+ |

The system requires a **stable internet connection** to fetch real-time stock data. Stock prices are **highly volatile**, and no model can **guarantee 100% accuracy**. The system **does not execute trades directly** but provides prediction for decision-making.

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#### 7. Conclusion

Through this machine learning project, we may draw the conclusion that there are numerous factors to consider when training a machine learning model, including cleaning the data and attempting to collect all the characteristics in an organised manner. We created a method for drowsy driving detection based on vision with the intention of alerting the driver. The technique to pinpoint the eyes and track weariness is non- invasive. A custom image processing method is used to establish where the eyes are. The technology can tell if the eyes are open or closed while it is monitoring. A warning signalis sent when the eyes are closed for an extended amount of time. The following conclusions were made:

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