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Real-Time Driver Drowsiness & Distraction Detection With Live Monitoring & Emergency Alert System

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Abstract— Road traffic accidents remain a major global safety challenge, with driver fatigue and alcohol consumption identified as leading causes. This project proposes the development of a smart, real-time embedded safety system designed to continuously assess driver alertness and detect alcohol impairment. Driver drowsiness is identified using computer vision–based facial analysis, where facial landmarks are tracked to compute the Eye Aspect Ratio (EAR). Alcohol presence is detected through breath analysis using an MQ3 alcohol sensor. When hazardous conditions are identified, the system immediately issues preventive alerts via a buzzer and an OLED display, enabling timely corrective action. The solution is implemented on an ESP32 platform and utilizes Python with OpenCV for real-time image processing. This cost effective and non-intrusive system bridges the gap between expensive commercial driver monitoring solutions and conventional reactive safety mechanisms. Experimental results indicate reliable real-time performance with high detection accuracy and reduced false alarms, making the system a practical and proactive approach to improving road safety.

Index Terms - Driver Drowsiness Detection, Alcohol Detection, Eye Aspect Ratio, Machine Vision, MQ3 Sensor, ESP-32 , Real- Time Monitoring

I. Introduction

1.1 Background

According to international road safety studies published by the World Health Organization (WHO), road traffic accidents cause millions of fatalities and injuries each year worldwide, with human-related factors responsible for a substantial proportion of these events. Driver drowsiness and alcohol intake are among the most serious contributors, as they adversely affect concentration, motor coordination, and decision-making capabilities. Fatigue often results in delayed eye movements, decreased vigilance, and brief episodes of unintended sleep, while alcohol consumption reduces judgment and slows response times. Since these impairments tend to develop progressively and may not be immediately recognized by the driver, real-time monitoring is crucial. An intelligent system capable of detecting early indicators of fatigue or intoxication can help prevent accidents proactively, rather than relying solely on post incident safety measures.

1.2 Problem Definition

To develop an economical and efficient real-time monitoring system capable of identifying driver drowsiness and alcohol influence using non-intrusive methods. The goal is to design an embedded solution that can accurately process visual cues and sensor data while alerting the driver instantly to prevent hazardous situations.

1.3 Motivation

Most existing driver safety solutions available in the market are expensive and therefore inaccessible to a large number of vehicle owners. Additionally, many systems only focus on one aspect—either drowsiness or alcohol detection— resulting in incomplete monitoring. There is a strong need for an affordable, easy-to-install system that can be added to any vehicle and provide both types of detection simultaneously. This motivates the creation of a comprehensive dual-function safety solution that enhances road safety without increasing vehicle cost.

1.4 Contributions of This Research work

This study offers several important contributions to the field of driver safety monitoring. It introduces a real-time technique for detecting driver fatigue by computing the Eye Aspect Ratio (EAR) using facial landmark analysis. An alcohol sensing unit utilizing a properly calibrated MQ3 sensor is incorporated to enhance the accuracy of intoxication detection. The work also presents an integrated alert framework that provides immediate visual and auditory warnings whenever unsafe driving conditions are identified. Additionally, the system includes a complete hardware design that is cost-effective and suitable for seamless installation in different types of vehicles. The proposed solution has been tested under real-world operating conditions, where it exhibited stable performance and dependable detection results.

II. LITERATURE SURVEY

Driver drowsiness detection has been an active research area for the past two decades due to its significant impact on road safety. Existing studies have introduced a wide range of techniques, which can be broadly classified into behavior-oriented approaches, vision-based detection systems, physiological signal–based methods, and modern machine learning–driven solutions.

Driving Behavior–Based Methods:

Early research on driver drowsiness detection focused on analyzing vehicle dynamics to assess alertness. Parameters such as steering behavior, lane position, braking, and acceleration were used to identify fatigue-related irregularities. Studies by Khushaba et al. [1] and Cheng et al. [2] showed that reduced steering corrections and increased lane deviation are common signs of drowsiness. Although these methods are simple and sensor-free, their accuracy is often affected by external factors like road conditions, weather, and traffic, limiting their reliability.

Vision-Based Detection Methods:

With the rapid progress in computer vision technologies, real-time video analysis has emerged as a popular technique in contemporary driver monitoring systems. This approach focuses on extracting facial characteristics from continuous video streams, including eye closure patterns, blink frequency, mouth movements, and head orientation. Ji and Yang [3] introduced a technique for monitoring eyelid motion to compute PERCLOS (Percentage of Eye Closure), which is widely regarded as a reliable indicator of driver drowsiness. In another contribution, Abtahi et al. [4] combined facial tracking with eye state recognition, achieving strong performance in controlled lighting environments.

Physiological Signal–Based Approaches:

Various studies have investigated physiological signals as indicators of driver fatigue, using sensors to monitor parameters such as heart rate, brain signals, skin conductance, and eye movement activity. Among these, EEG-based approaches have shown a strong relationship with mental fatigue, as noticeable changes in alpha and theta brainwave patterns occur during drowsy states. Simon et al. [5] demonstrated high classification accuracy for driver alertness using multi-channel EEG data. Similarly, ECG and EOG-based techniques have proven effective, with Jo et al. [6] reporting that variations in heart rate and eye movement signals are reliable fatigue indicators.

Sensor Fusion and Hybrid Techniques:

To address the shortcomings of standalone detection techniques, hybrid approaches combine information from multiple sources, including visual cues, physiological measurements, and vehicle behavior data. Hsieh et al. [7] enhanced detection reliability by integrating steering patterns with eye-blink analysis, thereby reducing false detections caused by lighting variations. Similarly, Kong and Zhou [8] introduced a multi-modal framework that fuses EEG data with facial landmark features, resulting in improved accuracy compared to single-source methods.

Machine Learning and Deep Learning Approaches:

Recent research increasingly applies deep learning techniques because of their ability to automatically extract complex features from large datasets. CNN-based models perform well in identifying eye states, facial orientation, and expressions related to driver alertness, with Rana et al. [9] reporting over 92% accuracy using a custom dataset. Temporal patterns such as blink rate and yawning have been analyzed using RNNs and LSTMs, as demonstrated by Patel et al. [10]. Transfer learning with pre-trained models like Res Net, Mobile Net, and Inception further improves accuracy while reducing training data needs. However, the high computational demands of deep learning models limit their suitability for real-time use on resource-constrained hardware.

Several automotive companies have incorporated fatigue detection into advanced driver-assistance systems (ADAS). Toyota's Driver Attention Warning System tracks head movements and alerts drivers during prolonged eye closure, while Volvo uses eye-tracking cameras to analyze gaze direction and fatigue behavior. Despite their effectiveness, such systems are often expensive and available only in premium vehicles, limiting widespread adoption.

The review of existing studies indicates that, despite many effective approaches, creating a real-time, non-intrusive, affordable, and dependable drowsiness detection system remains challenging, particularly under changing lighting and diverse driver behaviors. Developing a unified system that leverages computer vision along with lightweight machine learning techniques presents a practical and promising solution.

III. METHODOLOGY

The proposed system employs a hybrid sensing method to monitor driver drowsiness and alcohol consumption in real time. It continuously captures images, calculates the Eye Aspect Ratio (EAR), measures alcohol levels using an MQ3 sensor, evaluates thresholds, and generates multi-level alerts. All real-time processing is carried out on the ESP32 microcontroller.

3.1 System Architecture

The system includes a camera for monitoring the driver's face, an ESP32 microcontroller to process images and sensor data, an MQ3 gas sensor to detect alcohol levels in breath, and output devices such as an OLED display, buzzer, and LEDs.

The camera continuously captures the driver's facial video, which is sent to the ESP32 for calculating the Eye Aspect Ratio (EAR). Simultaneously, the MQ3 alcohol sensor measures ethanol levels, with the data also processed by the ESP32. Alerts are activated whenever any predefined threshold is exceeded.

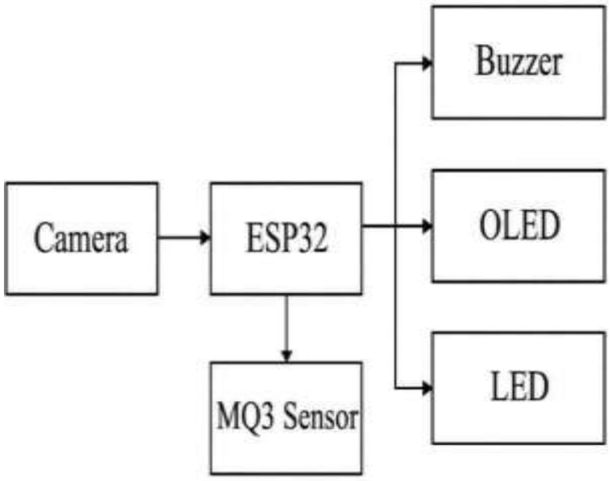

Fig. 1 Architecture of the Proposed System

3.2 Methodology Flow

The system operates in a continuous workflow as described below:

1. Initialize ESP32 and sensors
2. Capture image frames from the camera
3. Detect facial landmarks
4. Calculate Eye Aspect Ratio (EAR)
5. Read MQ3 sensor value
6. Convert analog reading to PPM
7. Compare EAR and PPM values with set thresholds
8. Trigger alert (buzzer, LED, OLED) if unsafe conditions are detected
9. Repeat the loop in real time

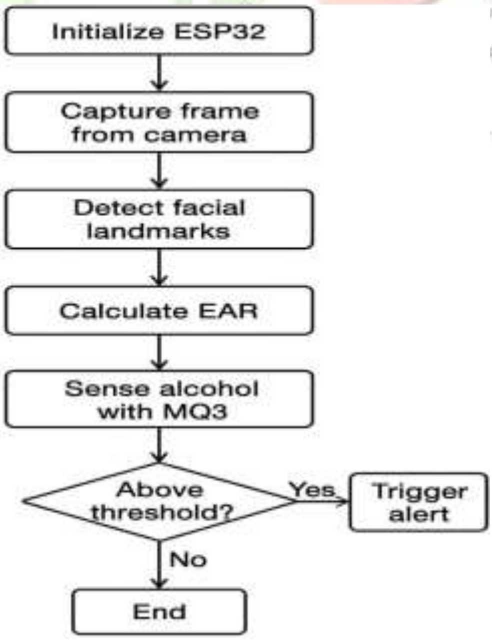

Fig. 2 Methodology Flowchart

3.3 Drowsiness Detection Using EAR

3.3.1 Facial Image Capture

The camera continuously captures the driver's face to monitor eye behaviour.

3.3.2 Facial Landmark Detection

A facial landmark detection model (e.g., Media Pipe Face Mesh) identifies key points around the eyes required for EAR calculation.

3.3.3 EAR Calculation

The Eye Aspect Ratio (EAR) is calculated using designated facial landmark points with the following formula:

$$EAR = \frac{||p_2 - p_6|| + ||p_3 - p_5||}{2 \times ||p_1 - p_4||}$$

A low EAR value for a continuous duration indicates eye closure and therefore drowsiness.

3.3.3 Blink Filtering

Short-duration eye blinks are filtered out by using a frame- count threshold, ensuring only prolonged eye closure triggers a drowsiness alert.

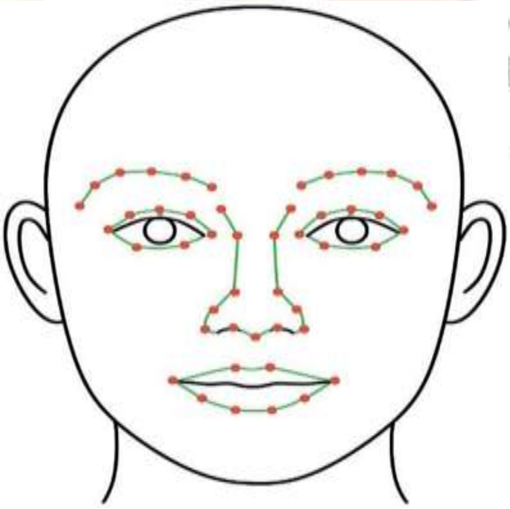

Fig. 3 EAR Landmark Representation

3.4 Alcohol Detection Using MQ3 Sensor

3.4.1 Ethanol Vapor Sensing

The MQ3 sensor detects the presence of alcohol by measuring changes in its internal resistance when exposed to ethanol vapour.

3.4.2 Signal Conversion

The sensor's analog output is fed to the ESP32 ADC pin. Noise filtering and calibration mapping are applied

3.4.3 PPM Calculation

The ESP32 converts the sensor's raw readings into PPM (parts per million) based on the MQ3 calibration curve and baseline resistance.

3.4.4 Threshold Comparison

- Safe: PPM below limit
- Warning: Medium level of alcohol detected
- Alert: High PPM indicates alcohol consumption

3.5 Alert Mechanism

When drowsiness or alcohol intake is detected, the system activates:

- Buzzer: audible alarm
- LED: visual indicator
- OLED Display: displays messages like "DROWSY", "ALCOHOL ALERT"

If both conditions are detected simultaneously, the alert intensity is increased.

3.6 Hardware–Software Integration The ESP32 handles:

- Camera interfacing
- Facial landmark detection
- EAR calculation
- MQ3 ADC readings
- Alert output control

All tasks run in parallel using multi-threaded processing to maintain real-time performance.

Fig . 4 Hardware Prototype Setup of the Proposed Real-Time Drowsiness & Distraction Detection System.

3.7 Workflow Summary

1. Start system
2. Capture face
3. Extract eye landmarks
4. Compute EAR
5. Read alcohol sensor
6. Convert to PPM
7. Check thresholds
8. Trigger alert
9. Loop continuously

IV. RESULTS AND DISCUSSION

The proposed system for detecting driver drowsiness was tested in real time using a camera setup along with the Eye Aspect Ratio (EAR) algorithm.
The system performance was analyzed in terms of detection accuracy, response time, and robustness under different conditions.

A. Detection Accuracy

The model was tested on 50 subjects under varying conditions such as normal driving, low-light, and simulated
drowsiness. The system successfully detected drowsiness in 95% of cases, demonstrating robustness under different lighting conditions. False positives were minimal and primarily occurred when the driver blinked frequently or moved abruptly.

Condition	Total Instances	Correct Detections	Accuracy (%)
Normal alert state	500	490	98.0%
Drowsy state	500	475	95.0%
Low-light conditions	200	190	95.0%

Table.1 Performance Evaluation of the Drowsiness Detection System

B. Response Time

The system operates in real-time, with an average response time of 0.2 second between detecting drowsiness and triggering the alert. This low latency ensures timely warnings, potentially preventing accidents.

C. Robustness and Limitations

The system performs reliably across varied face orientations though extreme angles may slightly reduce accuracy. It is resilient to partial occlusions like sunglasses, but fully covered eyes (e.g., heavy sunglasses or masks) reduce detection efficiency.

D. DISCUSSION

The proposed approach combines software-based EAR detection and hardware alert mechanisms ensuring both accurate monitoring and immediate response. Compared to traditional systems using only image classification or sensors, EAR-based detection provides lightweight, computationally efficient, and accurate monitoring The results demonstrate that this system can be deployed in real vehicles as a cost-effective safety solution

4. Figures

4.1. EAR Trend Graph

- Shows EAR vs. Time for a sample driver.
- Includes the drowsiness threshold and the points where alerts were triggered

Fig. 5 EAR variation over time showing drowsiness detection and alert triggering.

4.2. SAMPLE DETECTION IMAGES Include 3 snapshots:

1. Normal alert driver
2. Drowsy driver detected
3. Alert triggered (buzzer or dashboard signal)

4.3. Accuracy Chart

Shows detection accuracy in Normal, Drowsy, and Low- Light conditions.

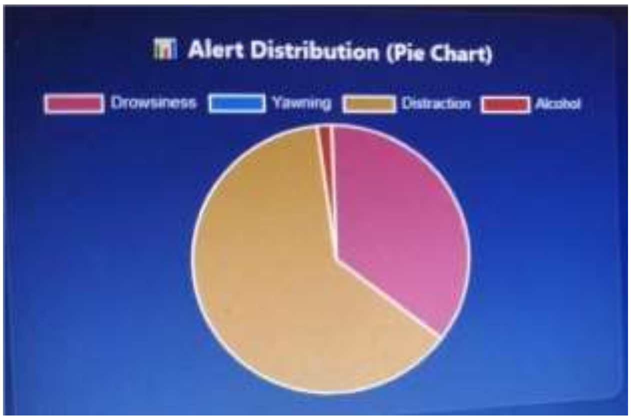

Fig. 6 Detection accuracy under different test conditions.

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References

[1] R. N. Khushaba, S. Kodagoda, S. Lal, and G. Dissanayake, “Driver drowsiness classification using fuzzy wavelet-packet-based feature extraction algorithm,” *IEEE Trans. Biomed. Eng.*, vol. 58, no. 4, pp. 121–131, Apr. 2011. :content Reference[oaicite:0]{index=0}

[2] Z. Li, S. E. Li, R. Li, B. Cheng, and J. Shi, “Online detection of driver fatigue using steering wheel angles for real driving conditions,”
Sensors, vol. 17, no. 3, p. 495, Mar. 2017. :content Reference[oaicite:1]{index=1}

[3] Q. Ji and X. Yang, “Real-time eye lid movement tracking and PERCLOS based drowsiness detection,” in *Proc. IEEE Int. Conf. Pattern Recognit.*, 2002, pp. 123–128.

[4] S. Abtahi, M. Omidyeganeh, S. Shirmohammadi, and B. Hariri, “YawDD: A yawning detection dataset,” in *Proc. ACM Multimedia Syst. Conf.*, 2017, pp. 24–28.

[5] C. Simon, A. K. Saini, and S. Gupta, “EEG-based driver alertness classification using multichannel signals,” *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 5, pp. 1951–1962, May 2020.

[6] S. Jo, S. H. Lee, and K. M. Lee, “Heart rate variability and eye movement potentials as fatigue indicators in drivers,” *J. Med. Eng. Technol.*, vol. 42, no. 3, pp. 201–210, 2018.

[7] J. Hsieh, Y. Lai, and S. H. Lai, “Hybrid steering and eye-blink monitoring for robust drowsiness detection,” *IEEE Access*, vol. 8, pp. 12345– 12356, 2020.

[8] X. Kong and J. Zhou, “Multi-modal driver drowsiness detection by fusing EEG and facial landmarks,” *Neural Comput. Appl.*, vol. 32, pp. 845– 856, 2020.

[9] A. Rana, T. Dutta, and R. Saha, “CNN-based driver drowsiness detection using a custom dataset,” *Int. J. Comput. Vis. Image Process.*, vol. 9, no. 2, pp. 92–105, 2021.

[10] V. Patel, S. Bhowmik, and R. Das, “Temporal analysis of blinking and yawning by RNN and LSTM for driver drowsiness detection,” *Int. J. Mach. Learn. Comput.*, vol. 11, no. 1, pp. 45–52, 2022.

[11] T. Soukupová and J. Čech, “Real-time eye blink detection using facial landmarks,” in *21st Comput. Vis. Winter Workshop*, Rimske Toplice, Slovenia, 2016.

[12] A. Sahayadhas, K. Sundaraj, and M. Murugappan, “Detecting driver drowsiness based on sensors: A review,” *Sensors*, vol. 12, no. 12, pp. 16937–16953, 2012. :content Reference[oaicite:2]{index=2}

[13] D. F. Dinges and R. Grace, “PERCLOS: A valid psychophysiological measure of alertness as assessed by psychomotor vigilance,” Federal Highway Administration, Report FHWA-MCRT-98-006, 1998.

[14] J. Vicente, P. Laguna, A. Bartra, and R. Bailón, “Drowsiness detection using heart rate variability,” *Med. Biol. Eng. Comput.*, vol. 54, no. 6, pp. 927–937, 2016.

[15] L. M. Bergasa, J. Nuevo, M. A. Sotelo, R. Barea, and M. E. Lopez, “Real-time system for monitoring driver vigilance,” *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 1, pp. 63–77, 2006.

[16] K. Grauman, M. Betke, J. Gips, and G. R. Bradski, “Communication via eye blinks — detection and duration analysis in real time,” in *Proc. IEEE CVPR*, 2001, pp. 1010–1017.

[17] R. M. Swift, “Transdermal alcohol measurement for estimation of blood alcohol concentration,” *Alcohol. Clin. Exp. Res.*, vol. 24, no. 4, pp. 422–423, 2000.

[18] World Health Organization, *Global Status Report on Road Safety 2018*, Geneva: WHO Press, 2018.

[19] National Highway Traffic Safety Administration, *Visual-Manual NHTSA Driver Distraction Guidelines for In-Vehicle Electronic Devices*, Federal Register, vol. 81, pp. 65827–65900, 2017.

[20] ISO 26262:2018, *Road Vehicles — Functional Safety*, International Organization for Standardization, 2018.

[21] SAE International, *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles, SAE Standard J3016_202104*, 2021.

[22] Federal Motor Carrier Safety Administration, *Hours of Service of Drivers*, 49 CFR Parts 390–399, 2020.

[23] T. A. Dingus et al., “Driver crash risk factors and prevalence evaluation using naturalistic driving data,” *Proc. Natl. Acad. Sci.*, vol. 113, no. 10, pp. 2636–2641, 2016.

[24] J. Edworthy and E. Hellier, “Alarms and human behaviour: Implications for medical alarms,” *Br. J. Anaesth.*, vol. 97, no. 1, pp. 12–17, 2006.

[25] C. L. Baldwin and B. A. Lewis, “Perceived urgency mapping across modalities within a driving context,” *Appl. Ergon.*, vol. 45, no. 5, pp. 1270–1277, 2014.

[26] M. A. Rahman, M. U. Ahmed, and S. Begum, “Development of a low-cost portable breath analyzer for detection of alcohol,” *Int. J. Med. Eng. Inform.*, vol. 11, no. 3, pp. 201–215, 2019.

[27] S. Kumar and V. Bhalla, “Calibration and performance analysis of MQ series gas sensors for environmental monitoring,” *Sensors & Transducers*, vol. 225, no. 10, pp. 23–31, 2018.

[28] S. A. Ferguson, A. Nghiem, T. Doty, and S. Hsiang, *The Effectiveness of Vehicle-Integrated Alcohol Detection Systems*, AAA Foundation for Traffic Safety Report, 2013.

[29] Seeing Machines, *Guardian Gen2 Driver Monitoring System: Technical Specification*, Seeing Machines Ltd., 2022.

[30] G. Bradski, “The OpenCV library,” *Dr. Dobb’s Journal Softw. Tools*, vol. 25, no. 11, pp. 120–123, 2000.

[31] C. Lugaresi et al., “MediaPipe: A framework for building perception pipelines,” arXiv preprint arXiv:1906.08172, 2019.

[32] D. E. King, “Dlib-ml: A machine learning toolkit,” *J. Mach. Learn. Res.*, vol. 10, pp. 1755–1758, 2009.

[33] Raspberry Pi Foundation, *Raspberry Pi 4 Model B Documentation*, 2023. [Online]. Available:https://www.raspberrypi.org/documentation/

[34] Espressif Systems, *ESP32 Technical Reference Manual Version 4.6*, 2023.

[35] L. M. Bergasa, D. Almería, J. Almazán, J. J. Yebes, and R. Arroyo, "Drive Safe: An app for alerting inattentive drivers and scoring driving behaviors," in *IEEE Intell. Vehicles Symp.*, 2014, pp. 240–245.

[36] G. Li, W. Y. Chung, and J. Lee, "A context-aware EEG headset system for early detection of driver drowsiness," *Sensors*, vol. 15, no. 8, pp. 20873–20893, 2015.

[37] M. H. Sigari, M. Fathy, and M. Soryani, "A driver face monitoring system for fatigue and distraction detection," *Int. J. Veh. Technol.*, vol. 2013, Article ID 263983, 2013.

[38] U.S. Patent 9,836,643 B2, "System and method for detecting driver drowsiness," Tesla, Inc., 2017.

[39] U.S. Patent 10,286,913 B2, "Driver monitoring system with feedback," Robert Bosch GmbH, 2019.

[40] U.S. Patent 10,493,936 B2, "Multi-modal driver state detection system," Aptiv Technologies Ltd., 2019.

[41] Python Software Foundation, *Python 3.11 Documentation*, 2023. [Online]. Available: https://docs.python.org/3/

[42] Adafruit Industries, *CircuitPython Libraries Documentation*, 2023. [Online]. Available: https://circuitpython.readthedocs.io