AIoT-Based Mental Fitness Detection System

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***Abstract*—This paper puts forth an AIoT-concentrated wellness discovery system aimed at measuring one's mental and physical readiness to undertake fundamental tasks like working equipment. The system utilizes an Fake Neural Organize (ANN) exhibit pre-trained on a database with readings from an MQ-3 sensor (for alcohol content), a GSR sensor (for push testing), and a MAX30102 sensor (for heart rate and SpO2 monitoring). The trained ANN show is then used to generate anticipations on real-time data gathered via an ESP32 microcontroller. Live sensor data is ready and transmitted to a Flask-based server enabling the ANN demonstrate, which determines if the individual is fit or unfit. Identified outcomes can be displayed on an DashBoard or Mobile Application. This small, affordable structure ensures safety by providing handy estimates of a person's healthiness for critical tasks.**

***Index Terms*—ANN, AIoT, MQ-3 Sensor, MAX30102, GSR Sensor, ESP32, Carafe Server, Mental Wellness Discovery.**

I. Introduction

Mental well-being has a central role in ensuring an individual's readiness to carry out safety-critical tasks like operating equipment. Factors like alcohol use, elevated push levels, and abnormal heart conditions can incapacitate a human's mental and physical capability. This essay suggests an AIoT-based mental well-being location system that monitors significant physiological parameters in real time with embedded sensors and machine learning. The project employs an MQ-3 sensor to detect liquor concentration, a GSR sensor to measure stretch based on skin conductivity, and a MAX30102 sensor to quantify heart rate and SpO2 levels. A pre-trained Counterfeit Neural Organize (ANN) demonstrate, implemented on a Jar server, processes the real-time sensor data gathered by an ESP32 microcontroller. From this, the ANN anticipates if the individual is capable or not capable of executing tasks needing mental center. The outcome is displayed on an DashBoard or Mobile application, empowering timely alarms and choice-making. This small and economical framework gives a proactive solution to advance security and productivity in various real-world applications.

Internet of Things (IoT) has become a strong means to integrate embedded hardware, sensors, and cloud services to make intelligent, real-time decision-making systems possible. This paper proposes an IoT-based multi-sensor driver monitoring system capable of detecting possible signs of driver impairment through physiological signals and providing alerts prior to any critical condition developing. The device consists of three main sensors: the MQ-3 alcohol vapor gas sensor for sensing alcohol from the driver's lungs, the MAX30102 for monitoring heart rate and blood oxygen saturation (SpO2), and the GSR (Galvanic Skin Response) sensor that monitors stress levels by detecting changes in skin conductivity. The sensors are connected to either an ESP32 microcontroller or a Raspberry Pi, which serves as the system's processing unit. The controller continuously gathers and processes data from the sensors. As soon as it finds abnormal values—like increased alcohol levels, raised stress, or abnormal heart rate—the system sends instant alerts. The alerts are shown on a DashBoard and also pushed to a mobile , enabling remote users like family members or emergency personnel to act promptly. The system proposed prioritizes affordability, portability, and real-time response. In contrast to traditional models, it is not based on a single metric and is not limited to vehicle ignition control. Rather, it is targeted at early detection and response, allowing for improved prevention of possible accidents. The modular architecture facilitates scalability and can further be included in smart vehicle systems or wearable devices.

II. Background

Conventional safety features in vehicles like airbags, seatbelts, and anti-lock braking systems only react once an accident has happened. In the same way, breath testers and single-sensor systems for evaluating drivers are intrusive, simple to circumvent, or capable of detecting only one form of impairment. Physiological indicators like heart rate, skin conductivity, and respiratory composition provide more reliable data for a driver's physical and mental status. They are dynamic, difficult to mimic, and give real-time information about stress, tiredness, or intoxication—important causes of road accidents. Emerging technologies in miniaturized biomedical sensors and IoT hardware platforms such as ESP32 and Raspberry Pi have made it possible to create low-cost, non-invasive, and compact health monitoring systems. The system can monitor several parameters continuously and send alerts prior to the critical situation.Combining multi-sensor input with real-time processing and wireless communication, IoT-based solutions provide an active solution for driver safety, changing the context from reactive to preventive intervention.

III. Objective

To design and implement an AIoT-based system that can properly identify a person's mental and physical readiness to drive or work machinery before/after drinking alcohol..

IV. Materials and Equipment

The AIoT-based driver monitoring system was designed using a mix of physiological sensors, embedded controllers, and wireless communication devices. An MQ-3 gas sensor was used to determine the presence of alcohol in the driver's breath at high sensitivity. In the system, a MAX30102 sensor was used for capturing vital signs and accurately determined heart rate and blood oxygen saturation (SpO2).In addition, a GSR sensor was used to measure the stress levels of the driver by detecting skin conductivity changes, which are indicative of emotional and physiological arousal. For data processing and communication, either a Raspberry Pi or an ESP32 microcontroller was utilized as the master control unit. Both platforms offered excellent support for sensor interfacing and real-time data processing, with onboard Wi-Fi allowing easy wireless communication with a mobile app. The primary output interface was an OLED display module that displayed live physiological information and alarms. It was complemented by a remote notification and monitoring mobile app.

A regulated 5V power supply, jumper wires, and a breadboard were the fundamental building blocks that finished the hardware setup. These components helped make the system modular in nature, compact, and easy to use, making it ideal for real-time operations in vehicular environments. The multiple communication interfaces and multiple biosensors facilitated complete monitoring of the physical and cognitive state of the driver.

V. Methodology

A. AIoT Data Preprocessing – Step-by-Step Breakdown

The following steps outline the complete workflow of the AIoT-based driver monitoring system:

1) **Dataset Collection and Labeling:** A dataset comprising physiological parameters such as alcohol level, heart rate, SpO2, and GSR is collected under both normal and impaired conditions. Each entry is labeled to indicate whether a person is fit enough to perform a specific task or not.
2) **Feature Engineering and Normalization:** Raw data is preprocessed to extract key statistical or time-based features. The values are normalized to ensure consistency across both training and real-time inputs.
3) **Model Training:** A machine learning classification models used ANN,SVM and Random Forest is trained using the labeled dataset to distinguish between "Fit" and "Impaired" driver states.
4) **Model Deployment:** The trained and optimized model is exported and embedded into the ESP32 or Raspberry Pi environment for real-time inference during deployment.
5) **Sensor Initialization:** Power is supplied to the MQ-3, MAX30102, and GSR sensors. Each sensor is initialized and calibrated to provide stable baseline readings for breath alcohol, heart rate, oxygen saturation, and skin conductivity.
6) **Live Data Acquisition:** Continuously collect real-time sensor data: - MQ-3: Breath alcohol concentration - MAX30102: Heart rate (BPM) and SpO2 - GSR: Skin conductivity representing stress levels
7) **Data Preprocessing:** Incoming raw data is cleaned, scaled, and formatted to match the structure used during model training.
8) **Model Prediction:** The preprocessed sensor data is input into the trained model. The model classifies the driver as either "Fit" or "Unfit."
9) **Output Alerts:** If the driver is classified as "Impaired," warning messages are displayed on the DashBoard and alerts are transmitted to a mobile application via Wi-Fi.
10) **Continuous Monitoring Loop:** The system repeats the sensing, prediction, and alerting cycle at regular intervals (e.g., every 2 seconds) for continuous monitoring.

B. Block Diagram

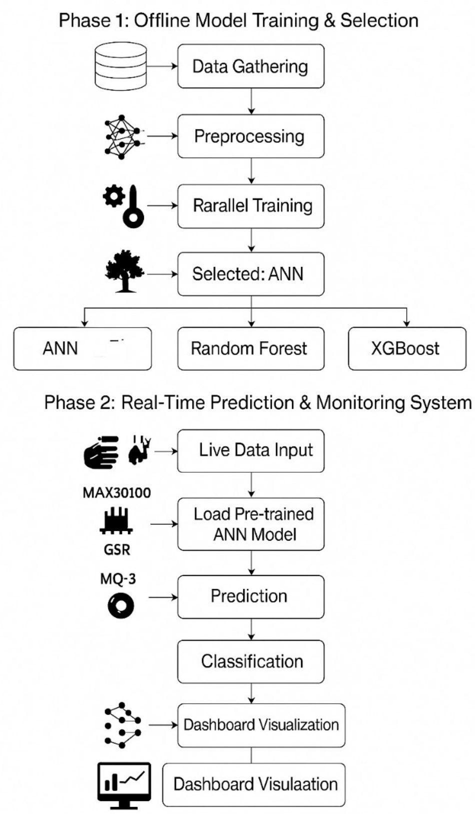

Fig. 1. Flow-Chart

C. Connectivity of Components

D. Model Used

Artificial Neural Network (ANN)

E. Fitness Evaluation

For every group of real-time physiological inputs, sensor data were contrasted with pre-set security thresholds. The driver was graded as "Fit" or "Unfit" depending on whether liquor level, push level, or vital signs exceeded worthy thresholds. These grades emerge, along with live sensor readings, were at the time displayed on the dashboard, providing rapid experiences for monitoring and evaluation.

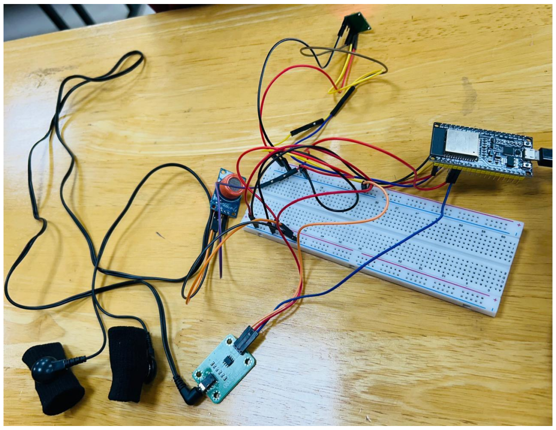

Fig. 2. Connection of Components

VI. Evaluation and Observation

A. Results

Fig. 3. AIoT-Based Mental Fitness Detection System: Real-Time Monitoring of Heart Rate, SpO2, Alcohol Level, and GSR for Enhanced Mental Health Insights.

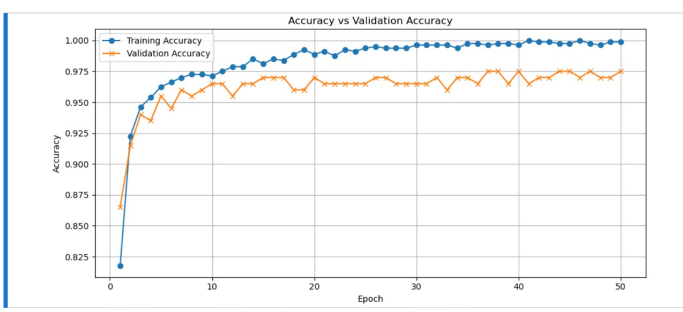

Fig. 4. Accuracy vs Validation Accuracy.

- The Artificial Neural Network (ANN) model demonstrated high accuracy in classifying driver states based on multi-sensor input features such as alcohol levels, heart rate, SpO2, and GSR.
- Proper pre-processing of sensor data—such as normalization, outlier removal, and signal smoothing—significantly enhanced model stability and performance.

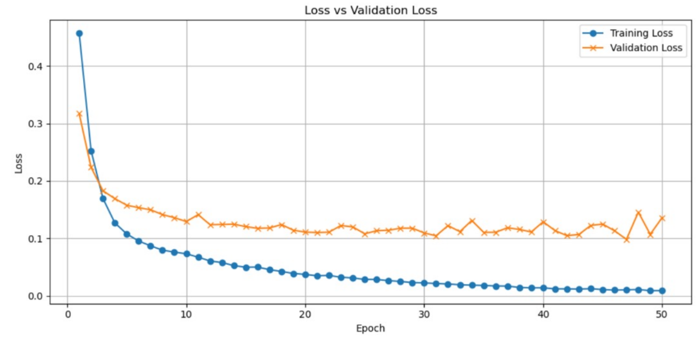

Fig. 5. Loss vs Validation Loss

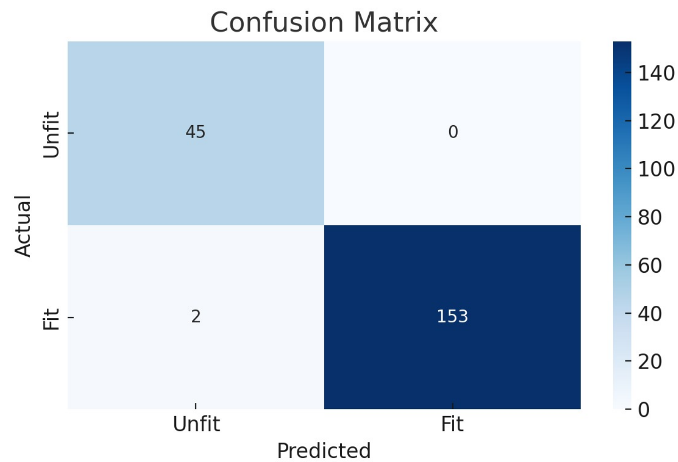

Fig. 6. Confusion Matrix

- Label encoding was used to convert categorical output classes (e.g., "Fit", "Impaired") into numerical form suitable for ANN training.
- The trained ANN model was saved enabling fast deployment and inference without retraining.
- The system showed strong generalization during testing, accurately identifying impaired or stressed conditions based on unseen real-time data inputs.

VII. Discussion

The suggested AIoT-based driver monitoring system has high potential to improve road safety by performing real-time physiological evaluation. In contrast to conventional techniques like ignition locks or alcohol breath tests independently, this system incorporates several biometric signals—breath alcohol level, heart rate, SpO2, and skin conductivity—to make a driver more comprehensive and accurate assessment of fitness. The multi-sensor approach reduces the possibility of spurious alarms and enhances accuracy in separating physical and cognitive impairment.

For enhanced real-world usefulness, subsequent releases need to add self-calibration routines, adaptive thresholds, and user-specific baselines to correct for individual variations. Additionally, the incorporation of machine learning algorithms

Precision	Recall	F1-Score	Accuracy
0.98	0.97	0.98	0.98
0.98	0.97	0.98	0.98

TABLE I
CLASSIFICATION REPORT FOR ANN MODEL

that are able to learn from patterns of individual behavior can render the system more responsive and resilient in the long term. Improvements on ESP32 or Raspberry Pi through edge computing will further minimize latency and enable offline decision-making when connectivity is not ideal.

VIII. CONCLUSION

In a world where a single moment of impaired judgment can cost lives, this AIoT-based mental fitness detection system offers a novel and intelligent approach to evaluating an individual's cognitive and physiological state under the influence of alcohol. By integrating multiple sensors—such as alcohol, GSR, heart rate, SpO2, and reaction time—and utilizing machine learning algorithms, the system goes beyond traditional alcohol detection methods that rely solely on BAC levels. It provides a comprehensive assessment of mental fitness, taking into account individual variability in tolerance and response. The solution is low-cost, portable, and adaptable for various applications, including driver monitoring, industrial safety, healthcare, and military readiness.

The ESP32 or Raspberry Pi-based prototype system is shown to be lightweight, affordable, and versatile. Real-time warnings through OLED display and mobile app further increase its usability in a range of areas including driver safety, industrial equipment operation, military preparedness, and healthcare screening. The modular design enables simple upgrades, such as the integration of machine learning algorithms and further sensors for detecting fatigue or drowsiness. This system is a potential advancement in utilizing AIoT to improve public safety and encourage responsible decision-making in alcohol-related or risky situations.

IX. FUTURE SCOPE

- Integration of fatigue and drowsiness detection using additional sensors like EEG or eye-blink monitoring.
- Development of personalized AI models that adapt to individual physiological baselines for improved accuracy.
- Deployment in wearable formats (e.g., smart bands or headsets) for increased portability and real-world usability.
- Real-time vehicle intervention, such as ignition blocking or emergency alerting, based on driver impairment detection.

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