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"Ai Based Predictive Maintenance And Anomaly Detection For Fleet Vehicles"

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Abstract- This project presents a low-cost AI and IoT-based predictive maintenance system for fleet vehicles using ESP32 and embedded machine learning techniques. The system continuously monitors important vehicle parameters such as temperature, vibration, speed, and GPS location using multiple sensors integrated with the ESP32 microcontroller. Sensor data is processed in real time and analyzed using a machine learning model developed with Edge Impulse Studio for anomaly detection and fault prediction. The system uses the Blynk IoT platform for cloud-based monitoring, live data visualization, and alert notifications. A Hall Effect sensor is used for speed detection, while the MPU6050 sensor measures abnormal vibrations in the vehicle system. The GPS module enables real-time vehicle tracking and location monitoring. During abnormal conditions, the system automatically activates buzzer and LED alerts and controls the motor through relay and MOSFET circuits for safety protection. The proposed system reduces unexpected breakdowns, minimizes maintenance costs, and improves operational efficiency and vehicle safety. The project is developed using affordable and easily available hardware components, making it suitable for smart transportation and industrial monitoring applications. The developed prototype demonstrates reliable real-time monitoring, intelligent fault detection, and remote fleet management capabilities.

Keywords: Predictive Maintenance, Fleet Vehicles, ESP32, IoT, Edge Impulse, Machine Learning, Blynk IoT, Fault Detection, GPS Tracking, Vibration Monitoring, Embedded Systems.

I. INTRODUCTION

Predictive maintenance is an advanced maintenance technique used to monitor the condition of machines and vehicles in real time. It helps in identifying faults before complete system failure occurs and reduces maintenance costs and downtime. Modern industries and fleet management systems require intelligent monitoring solutions for improving efficiency and safety. The combination of Artificial Intelligence (AI), Internet of Things (IoT), and embedded systems has made predictive maintenance more accurate and reliable. Sensors are used to continuously collect data related to temperature, vibration, speed, and location. This data is analyzed to detect abnormal conditions and prevent unexpected failures.

In this project, an AI-based predictive maintenance system for fleet vehicles is developed using ESP32, multiple sensors, and IoT technology. The system uses sensors such as DS18B20 for temperature monitoring, MPU6050 for vibration analysis, Hall Effect sensor for speed detection, and GPS module for location tracking. The collected sensor data is processed using machine learning techniques developed with Edge Impulse Studio for intelligent fault detection. Real-time monitoring and visualization are achieved through the Blynk IoT platform. The system can automatically detect abnormal conditions and generate alerts for safety purposes. It also controls the motor operation during fault conditions using relay and MOSFET circuits.

II. LITERATURE SURVEY

Predictive maintenance systems have become an important research area in modern industries and smart transportation systems. Traditional maintenance techniques mainly depend on manual inspection and scheduled servicing, which may not effectively prevent sudden equipment failures. To overcome these limitations, researchers have developed IoT-based monitoring systems that continuously collect machine data using various sensors. Parameters such as temperature, vibration, speed, and pressure are monitored in real time to identify abnormal operating conditions. The use of embedded systems and wireless communication technologies has improved the efficiency, reliability, and remote accessibility of predictive maintenance applications. These systems help reduce maintenance costs, downtime, and unexpected failures in industrial and transportation environments.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have significantly improved fault detection and anomaly prediction capabilities in predictive maintenance systems. Researchers have implemented machine learning algorithms to analyze sensor data patterns and detect faults before complete system failure occurs. AI-based monitoring systems provide better accuracy compared to tradit ional threshold-based methods. Platforms such as Edge Impulse Studio and TensorFlow Lite Micro are widely used for developing lightweight machine learning models for embedded devices. These AI models can run directly on microcontrollers with low power consumption and real-time processing capabilities. Such intelligent systems are increasingly used in industrial automation, smart manufacturing, and vehicle health monitoring applications.

III. PROPOSED METHODOLOGY

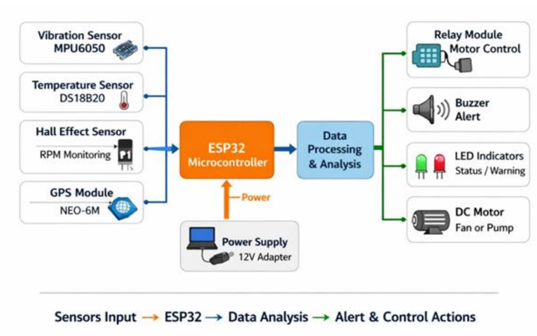

Figure 1: Ai-Based Predictive Maintenance And Anomly Detection For Fleet Vehicles

The methodology for this AI-based predictive maintenance system follows a structured TinyML and IoT pipeline designed to monitor fleet vehicle conditions and detect faults in real time using embedded edge devices. This workflow ensures that intelligent fault detection and remote monitoring can function efficiently without the need for high-end computing systems or continuous cloud processing.

1. Data Acquisition and Preprocessing

The process begins with the collection of real-time sensor data from fleet vehicles using multiple sensors connected to the ESP32 microcontroller. Sensors such as DS18B20, MPU6050, Hall Effect sensor, and GPS module continuously monitor important parameters including temperature, vibration, speed, and vehicle location. To ensure reliable processing and accurate fault analysis, the collected sensor data undergoes preprocessing steps such as:

- Sensor Calibration: Adjusting sensor readings to improve measurement accuracy and reduce noise.
- Data Normalization: Scaling sensor values to a standard range for stable AI model performance.
- Real-Time Filtering: Removing unwanted fluctuations and abnormal spikes from sensor readings.

2. Model Development and Training

A lightweight machine learning model is developed using sensor datasets collected under normal and fault conditions. The AI model is trained using Edge Impulse Studio to classify machine conditions and identify abnormal behavior patterns. The training process focuses on analyzing vibration and temperature variations to distinguish between healthy operating conditions and potential fault conditions in fleet vehicles. The trained model provides intelligent predictive maintenance capabilities with improved accuracy compared to traditional threshold-based monitoring systems.

3. Optimization and Embedded Deployment
To ensure compatibility with the hardware limitations of the ESP32 microcontroller, the trained AI model is optimized for embedded deployment. The optimized model is converted into an Arduino-compatible library format suitable for edge inference on ESP32. This optimization process reduces memory usage and computational complexity while maintaining reliable fault detection performance. The lightweight AI model enables real-time processing directly on the embedded device without requiring cloud-based computation.

4. Edge Deployment and Real-Time Monitoring
The optimized AI model is integrated with the ESP32-based predictive maintenance system for real-time operation. The hardware integration includes multiple sensors, motor control circuits, relay modules, LEDs, buzzer alerts, and GPS tracking components.

IV. CIRCUITE DIAGRAM

The system architecture is centered around an ESP32-CAM module, utilizing an FTDI USB-to-Serial adapter for firmware deployment where the adapter's TX/RX pins are cross connected to the module's RX/TX pins. To manage the device lifecycle, Boot Mode Selection is handled by shorting GPIO 0 to GND for Programming Mode, while removing the jumper triggers Flash Boot Mode for application execution.

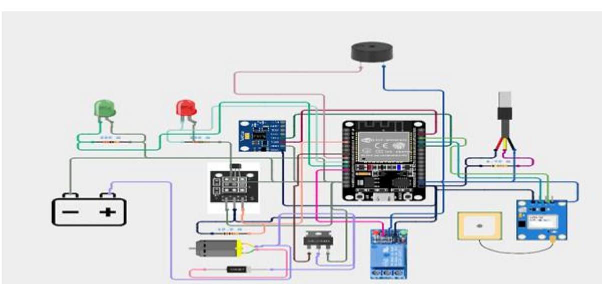

Figure 2: Circuite Diagram Of The System

Local telemetry is provided via a 0.91" OLED display interfaced through GPIO 14 (SDA) and GPIO 15 (SCL). Power is managed through a shared rail system distributing 3.3V/5V and GND from the FTDI source to all peripherals. This Compact Integration creates a streamlined footprint specifically optimized for Edge-AI applications, enabling high-performance visual recognition and real-time data logging within a localized hardware environment.

V. RESULT AND DISCUSSION

The developed AI-based predictive maintenance system for fleet vehicles was successfully implemented and tested using ESP32, multiple sensors, IoT monitoring, and embedded machine learning techniques. The system continuously monitored important parameters such as temperature, vibration, speed, and GPS location in real time. Sensor data collected from the DS18B20 temperature sensor, MPU6050 vibration sensor, Hall Effect sensor, and GPS module was processed efficiently by the ESP32 microcontroller. The system successfully transmitted live sensor data to the Blynk IoT platform through WiFi communication, enabling remote monitoring and visualization of vehicle conditions.

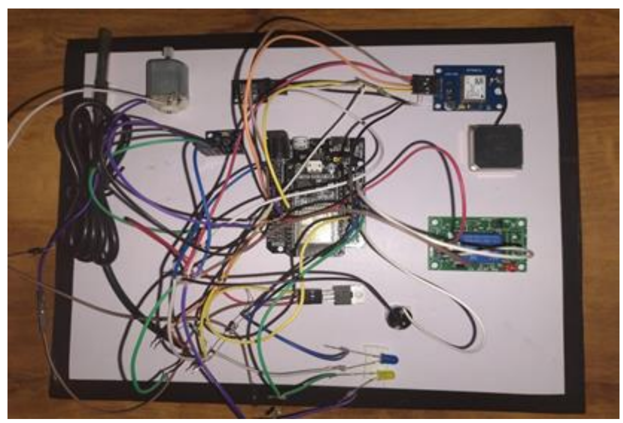

Figure 3: : Ai-Based Predictive Maintenance And Anomly Detection For Fleet Vehicles

The vibration and temperature monitoring system effectively identified abnormal operating conditions during testing. When sensor values exceeded predefined threshold limits, the AI-based fault detection system classified the condition as abnormal and activated safety mechanisms such as buzzer alerts, LED indicators, and automatic motor control using relay and MOSFET circuits. The GPS module successfully provided real-time latitude and longitude values for vehicle tracking and monitoring applications. The Blynk dashboard displayed live graphs, sensor values, and fault status updates, improving user accessibility and remote supervision capabilities.

The machine learning model developed using Edge Impulse Studio demonstrated effective anomaly detection performance for predictive maintenance applications. The integration of AI with IoT and embedded systems improved fault prediction accuracy compared to conventional monitoring methods. The proposed system reduced the possibility of unexpected breakdowns and improved operational safety through continuous monitoring and early warning alerts. The overall results confirmed that the developed prototype provides a low-cost, efficient, and reliable predictive maintenance solution suitable for smart transportation, industrial monitoring, and fleet management applications.

VI. CONCLUSION

The proposed AI-based predictive maintenance system for fleet vehicles was successfully developed using ESP32, multiple sensors, IoT technology, and embedded machine learning techniques. The system continuously monitored important parameters such as temperature, vibration, speed, and GPS location and transmitted real-time data to the Blynk IoT platform for remote monitoring and visualization. The machine learning model developed using Edge Impulse Studio effectively detected abnormal operating conditions and enabled intelligent fault prediction. During fault conditions, the system automatically activated buzzer alerts, LED indicators, and motor control mechanisms using relay and MOSFET circuits for safety protection. The developed system reduced maintenance costs, minimized unexpected breakdowns, improved operational safety, and demonstrated a reliable, low-cost, and efficient solution for smart fleet management and industrial predictive maintenance applications.

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REFERENCE

[1] Mobley, R. K. (2002). An Introduction to Predictive Maintenance. Butterworth- Heinemann.

[2] Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20(7), 1483–1510.

[3] Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18–23.

[4] Zhang, W., Yang, D., & Wang, H. (2019). Data-driven methods for predictive mainte- nance of industrial equipment: A survey. IEEE Systems Journal, 13(3), 2213–2227.

[5] Carvalho, T. P., et al. (2019). A systematic literature review of machine learning meth- ods applied to predictive maintenance. Computers & Industrial Engineering, 137, 106024.

[6] Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32.

[7] Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. IEEE Transactions on Industrial Informatics, 11(3), 812–820.

[8] Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273–297.

[9] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computa- tion, 9(8), 1735–1780.

[10] Liu, F. T., Ting, K. M., & Zhou, Z. H. (2008). Isolation forest. IEEE International Conference on Data Mining, 413–422.

[11] Sakurada, M., & Yairi, T. (2014). Anomaly detection using autoencoders with nonlin- ear dimensionality reduction. Proceedings of MLSDA, 4–11.

[12] Gubbi, J., et al. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. Future Generation Computer Systems, 29(7), 1645–1660.
[13] Wan, J., et al. (2018). Software-defined industrial Internet of Things in the context of Industry 4.0. IEEE Sensors Journal, 18(10), 4087–4096.
[14] Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. Mechanical Systems and Signal Processing, 115, 213–237.
[15] Khan, M. A., & Salah, K. (2018). IoT security: Review, blockchain solutions, and open challenges. Future Generation Computer Systems, 82, 395–411.