

# BRAKESHOE



# REPLACEMENT





## **Problem Statement**

## **Overview:**

Frequent brake failures are a critical safety concern, often leading to severe road accidents that result in injuries, fatalities, and financial losses. Brake-related issues rank among the top causes of vehicle collisions globally, highlighting gaps in existing vehicle maintenance systems. Currently, most maintenance practices are reactive, addressing brake issues only after they have occurred. This approach not only compromises safety but also escalates repair costs and vehicle downtime.

## Need:

There is an urgent need for a proactive, smart solution that can predict brake pad wear and potential failures by leveraging real-time sensor data and analyzing vehicle usage patterns. Reactive maintenance often allows brake pad issues to progress unnoticed, which can result in significant damage to other vehicle components, such as rotors, calipers, and even suspension systems. This cascading damage further increases repair costs and decreases the overall lifespan and reliability of the vehicle.



## **Project Objective**

## Goal:

Develop an IoT-enabled Smart Monitoring System for vehicle brake pads to revolutionize vehicle maintenance practices. This system embeds advanced sensors into brake pads to monitor their condition continuously. The data is sent in real-time to the vehicle's dashboard, notifying drivers of maintenance needs before failure occurs.

## **Core Features and Focus Areas:**

• **Proactive Maintenance:** Shift from reactive to predictive maintenance to prevent costly repairs and enhance vehicle longevity.

- Improved Safety: Early detection of brake issues minimizes the risks of accidents caused by brake failures.
- Real-Time Insights for Data-Driven Decisions: Data analytics powered by a Random Forest Algorithm processes the sensor inputs to accurately predict brake pad wear and the timing for replacement.
- Alert System: Notifications are delivered through vehicle dashboard signals, such as a blinking light or an auditory alert (e.g., beeping sounds), ensuring immediate driver awareness.



## **System Overview**

## **Overview:**

The system comprises sensors, an IoT gateway, an ML model, and an alert system. Acoustic Sensors detect abnormal noises, ATE Brake Pad Sensors measure pad thickness, and K-Type Thermocouples monitor temperature. The IoT gateway (e.g., Arduino or ESP32) transmits this data for analysis by a Random Forest algorithm, which predicts brake pad wear. Alerts are sent to the vehicle dashboard via lights or sounds, ensuring timely maintenance notifications.

## **Workflow:**

# Data Collection

Each sensor continuously collects data and sends it to the microcontroller.

## Data Processing

IoT gateway
processes and
transmits sensor
data

## Prediction

ML model predicts wear levels; alerts are generated

## Alert System

If brake wear surpasses a threshold, an alert is sent to the vehicle's dashboard.

## Data Storage

Cloud-based storage for model updates and historical insights.

## Sensor Placement and Installation

#### **Acoustic Sensor (Microphone):**

- Location: Installed near the brake assembly, often close to the caliper or disc pads.
- Purpose: Detects abnormal noises such as squealing or grinding caused by worn brake pads.
- Why Here? Acoustic vibrations propagate from the brake pads and discs during braking, making this location ideal for accurate sound capture.

#### **ATE Brake Pad Thickness Sensor:**

• Location: Embedded directly within the brake pad or positioned to measure pad thickness in real-time.

- Purpose: Continuously monitors the remaining thickness of the brake pad material.
- Why Here? Proximity ensures precise and continuous thickness measurement during braking operations.

### **K-Type Thermocouple:**

- Location: Attached near the brake disc or rotor.
- Purpose: Measures the temperature of the braking system to detect overheating and potential material degradation.
- Why Here? Braking generates heat due to friction between the brake pad and rotor; placing the sensor here ensures real-time monitoring.



## **Sensor Connectivity**

## **Sensor Connectivity Overview**

1.Hardware Integration: Sensors (acoustic, thickness, thermocouple) are connected to a microcontroller (e.g., Arduino, ESP32) via GPIO pins or analog inputs.

#### 2. Communication Protocols:

- a. I2C or SPI: For high-speed communication between sensors and the microcontroller.
- b. CAN Bus: For integration with the vehicle's internal systems.
- c. Wi-Fi or Bluetooth: For data transmission to the IoT Gateway or cloud.

- 3.Microcontroller Software: Use platforms like Arduino IDE or PlatformIO for sensor data handling and preprocessing.
- **4.Data Transmission:** Use MQTT or HTTP protocols to send data to the cloud.

#### **5.**Machine Learning Frameworks:

- **Python:** For ML model deployment using Scikit-learn or TensorFlow.
- Flask/Django: For setting up a lightweight server if required.

**6.IoT Platforms:** AWS IoT Core or Google Cloud IoT for remote data processing and storage.



## **Data Collection:**

Real-time data is gathered using embedded sensors within the vehicle's braking system:

- Acoustic Sensor: This sensor captures sound signals, identifying abnormal noises such as squealing or grinding, which indicate wear or potential damage to the brake pads.
- ATE Brake Pad Sensor: This sensor continuously monitors the thickness of the brake pads, providing data on wear levels.
- K-Type Thermocouple: Measures temperature changes during braking, which is crucial in understanding brake pad friction and potential overheating.

The sensors are connected to a microcontroller (e.g., Arduino, ESP32), which acts as an intermediary to collect and relay this data to the next layer of the system.

## **Data Processing:**

Once data is collected, it undergoes a processing phase to prepare it for analysis:

#### **Data Pre-processing:**

- Noise Filtering: Digital filtering techniques are applied to focus on relevant frequencies, such as the high-pitched squeals caused by wear.
- Normalization: The temperature and thickness data are normalized .
- Data Structuring: The collected data is structured to align sensor readings with time stamps and vehicle usage patterns.

#### **Data Transmission:**

The pre-processed data is sent to an IoT gateway (e.g., Raspberry Pi, ESP32) for aggregation. The gateway handles the transmission of this data to a local server or cloud-based infrastructure for further analysis.



## **Prediction Model**

ML prediction model for this project employs a Random Forest algorithm, which is an ensemble learning method based on decision trees. Here's how the process works:

#### **STEPS**

#### 1. Feature Selection and Engineering:

The model's input features come from real-time sensor data and then these features are normalized

#### 2. Training the Model:

The Random Forest algorithm builds multiple decision trees using bootstrap sampling, where each tree predicts brake wear based on features like thickness, temperature, and noise. Final predictions are made by aggregating outputs (e.g., majority voting for classification).

This method reduces overfitting by averaging predictions, improving generalization. Additionally, Random Forest uses **out-of-bag (OOB)** samples for built-in performance estimation, enhancing model reliability.

#### 3. Model Validation and Testing:

Model validation involves K-fold cross-validation to ensure generalizability and prevent overfitting. Key evaluation metrics include accuracy, precision, recall (for timely alerts), F1-score, and RMSE for continuous predictions.

#### 4. Predicting Brake Wear:

Based on thresholds for predicted wear (e.g., 20% remaining thickness), the system will issue a maintenance alert.

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## Features of the Machine Learning Model

### Data Handling:

Train-Test Split: The dataset is split into training (e.g., 80%) and testing (e.g., 20%) sets to evaluate the model's performance on unseen data.

### **Feature Engineering:**

- Acoustic frequency (Hz) from the microphone data.
- Normalized brake pad thickness from ATE sensors.
- Temperature readings aggregated into rolling averages for thermal stress patterns.

#### **Model Serialization:**

The trained Random Forest model is serialized using joblib or pickle for integration with the backend

#### **Threshold for Alerts:**

A probability threshold (e.g., 0.8) determines when to trigger alerts.

### **Model Training and Tuning:**

- Hyperparameter tuning is performed using Grid Search or Randomized Search to optimize parameters like the number of trees, max depth, and minimum samples per leaf.
- Cross-validation ensures robust performance and prevents overfitting.
- Out-of-Bag (OOB) Error Estimation: Direct performance evaluation of the model without additional datasets.
- Self-Learning: The system periodically retrains the model with new labeled data to improve accuracy.

## Software Development Kit (SDK)

#### 1. Sensor SDKs:

- Acoustic Sensors: Libraries like PyAudio for noise detection.
- Brake Pad Thickness: Use Arduino IDE or ESP32 SDK to capture sensor data.
- Temperature Sensors (Thermocouples): Adafruit libraries for reading temperature.

#### 2. Microcontroller SDKs:

• Arduino/ESP32 SDK: For sensor management, using MQTT to send data to the cloud.

#### 3. Machine Learning SDKs:

• Scikit-learn: For implementing the Random Forest algorithm. Libraries like NumPy, Pandas, and Matplotlib for data manipulation and visualization.

• TensorFlow/PyTorch: These frameworks provide extensive libraries for deep learning and ML model optimization

#### 4. Backend SDKs:

• Flask/FastAPI: Lightweight frameworks for building RESTful APIs to communicate between the sensors, the machine learning model, and the vehicle's dashboard system.

#### 5. Notification System SDKs:

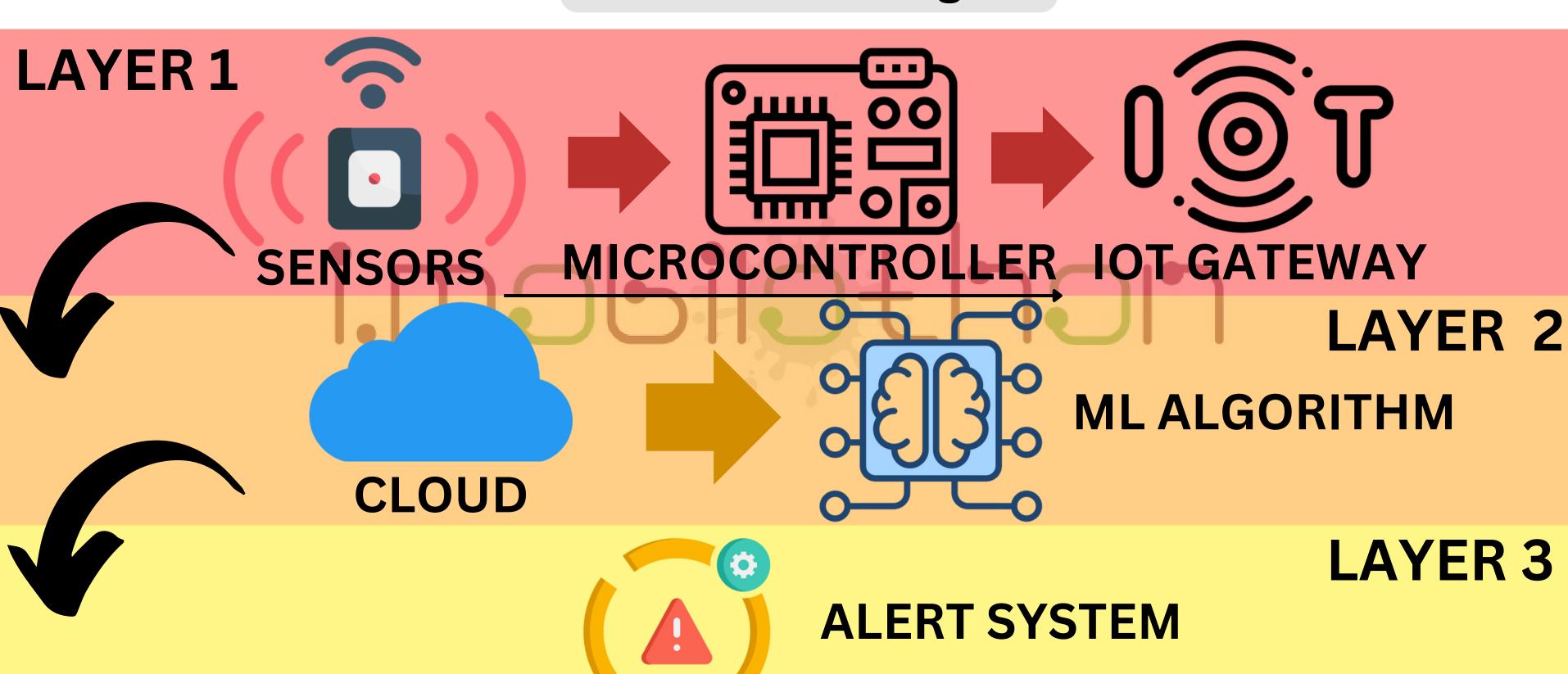
• FCM/Push Notifications: Firebase Cloud Messaging (FCM) for sending real-time alerts to mobile applications or car dashboard systems.

#### 6. Cloud & Edge Computing SDKs:

• AWS IoT Core: For data transmission and processing.



**Architectural Diagram** 





## Future Scope



**Expansion to Other Vehicle** 

Components: The AI-based predictive maintenance model can be expanded to monitor and predict the wear and tear of other critical vehicle components such as tires, engine belts, and suspension systems, enhancing overall vehicle safety and performance.

## **Conclusion**

The Brake Shoe Prediction Al Model uses real-time sensor data and machine learning to predict when brake shoes need to be replaced. This helps improve safety, cut down on maintenance costs, and prevent brake failures. By providing timely alerts, the model ensures better vehicle upkeep and has the potential to be applied to other car parts, making car maintenance smarter and more efficient.

## **Team Details**

**Team Name: Team Learners** 

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Vansh Kalra

#### **Team Members:**

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Replacement Prediction