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Deep Learning-Based Anomaly Detection Using MEMS Sensors

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Reliable condition monitoring during operation is of paramount importance for predictive maintenance. However, implementing such systems on compact and resource-constrained hardware remains challenging. This work presents a microcontroller-based sensing device that integrates MEMS motion and environmental sensors for real-world anomaly detection in mobile robots. The device operates at an output data rate of 250 Hz and streams field data wirelessly during operation. A dataset of 140 complete runs was collected, including five types of abnormal wheel operating conditions. A deep learning model based on the MLSTM-FCN architecture was trained on the raw sensor data to classify the robot's operational condition. The model achieved an overall accuracy of $94.4\,\%$ and a macro-F1 score of 0.93 on the test set. The results show that MEMS-based sensing combined with deep learning-based methods enables accurate and reliable anomaly detection on low-power embedded platforms. This provides a practical foundation for future predictive maintenance applications in industrial and robotic systems.

Keywords: Embedded Electronics, MEMS Sensors, Anomaly Detection, Predictive Maintenance, Deep Learning.

1. Introduction

Mobile robots are increasingly deployed in industrial, logistics, and service applications, where they operate autonomously in complex and dynamically changing environments Cognominal et al. (2021). Unlike stationary machinery, mobile robots are subject to varying speeds, surface conditions, payloads, and transient interactions, resulting in highly variable mechanical loads and motion patterns. As their operational roles expand, assessing the robot's operating state during normal use becomes essential for detecting emerging faults and enabling timely maintenance actions Zhang et al. (2023). Mechanical degradation in mobility-related components, particularly wheels, can lead to performance loss, increased energy consumption, or safety-critical failures Trojnacki and Dąbek (2019). At the same time, this operational variability complicates condition monitoring, as diagnostic methods developed for stationary industrial systems often struggle to generalize to mobile platforms operating under real-world conditions Koutsoupakis et al. (2023); Hassan et al. (2024).

Nevertheless, practical deployments increasingly require compact and low-power sensing solutions that can be embedded directly into robotic systems Vitolo et al. (2022). Recent advances in Micro-Electro-Mechanical Systems (MEMS) technology enable integrated sensing of motion and environmental parameters at relatively high sampling rates Algamili et al. (2021). However, the reliability of MEMS-based sensors under realistic operating conditions remains challenging due to noise, limited bandwidth, and constrained computational resources Shoaib et al. (2016). Deep learning–based methods address these challenges by learning representations directly from raw sensor data, allowing complex and non-stationary patterns to be captured without handcrafted features or extensive domain expertise Butte et al. (2018); Ma et al. (2021). This makes such approaches well suited for anomaly detection and predictive maintenance in mobile robots.

In this study, anomaly detection for mobile robots is investigated using an embedded MEMS-based sensing device and deep learning methods. A compact microcontroller-based sensor platform is deployed on a mobile robot to collect multimodal motion and environmental data during normal operation and under manually induced wheel fault conditions. The anomaly detection task is formulated as a supervised binary classification problem and addressed using a Multivariate Long Short-Term Memory Fully Convolutional Network (MLSTM-FCN) Karim et al. (2019); Ma et al. (2022) trained directly on raw sensor time-series data.

Primary contribution 1 (Embedded sensing system): This work demonstrates the feasibility of continuous, high-rate condition monitoring on a mobile robot using a compact and low-power MEMS-based sensing device under realistic and resource-constrained operating conditions.

Primary contribution 2 (Anomaly detection method): This study shows that an end-to-end deep learning approach can reliably capture non-stationary fault signatures from raw multi-modal sensor data without relying on handcrafted features, despite operational variability and sensor noise.

Secondary contribution (Dataset): A labeled real-world dataset is provided, comprising normal operation and multiple manually introduced wheel fault scenarios, enabling systematic evaluation of anomaly detection methods for mobile robotic systems.

2. Related Work

Vibration-based condition monitoring (VBCM) is a well-established approach for industrial machinery health assessment. Piezoelectric accelerometers remain the dominant sensing technology due to their high bandwidth and measurement accuracy, enabling reliable detection of bearing and gearbox faults Hassan et al. (2024); Dabrowski (2016). However, their cost, size, and power requirements often limit their applicability in compact or mobile systems.

To address these limitations, several studies have explored the use of MEMS accelerometers as a low-cost alternative. Comparative studies have shown that, despite higher noise density, MEMS sensors can achieve reliable fault detection when combined with appropriate signal processing Ompusunggu et al. (2021). Wireless vibration monitoring systems based on embedded sensors have also been demonstrated in long-term deployments Zanelli et al. (2023), highlighting their potential for distributed condition monitoring.

Traditional VBCM approaches rely on handcrafted features extracted from time and frequency domains, such as Root-Mean-Square (RMS) values, spectral components, and envelope analysis Sepulveda and Sinha (2020). Advanced techniques, including wavelet-based methods, have been proposed to handle non-stationary vibration signals and improve fault classification accuracy Amin et al. (2023). While effective, these methods require careful feature design and domain expertise.

More recently, machine learning and deep learning methods have been applied to reduce dependence on manual feature extraction Ma et al. (2024). Classical approaches using engineered features and support vector machines achieve moderate classification performance Ahmad et al. (2020), while deep learning models such as LSTM and CNN architectures have demonstrated superior accuracy by learning directly from raw vibration data Chen et al. (2023); Mukherjee et al. (2022). However, many of these studies rely on laboratory datasets, stationary systems, or high-performance sensing hardware.

Despite these advances, practical validation of end-to-end deep learning approaches using embedded MEMS sensing under realistic operating conditions remains limited. This work addresses this gap by experimentally evaluating a MEMS-based sensing system combined with a deep learning model on real-world data collected from a mobile robotic platform.

3. Methodology

This section describes the overall methodology adopted in this study, including the embedded sensing architecture, the data collection process on the mobile robot, and the deep learning–based approach used for anomaly detection.

3.1. *System Architecture*

The system architecture, shown in Fig. 1, follows a modular design that separates sensing, embedded processing, and data analysis. Motion and environmental data are acquired using the Arduino Nicla Sense ME, which integrates MEMS sensors for acceleration, angular rate, temperature, humidity, and pressure. The Nicla Sense ME operates as a sensor node and is connected via an I²C-based ESLOV interface to a Portenta H7 microcontroller, which serves as the central processing unit. The Portenta H7 buffers incoming sensor data and streams it wirelessly using the MQTT protocol Naik (2017) over Wi-Fi. A local MQTT broker (Mosquitto) distributes the data to multiple clients. Incoming data is stored locally and in a database backend (MongoDB), enabling both offline analysis and real-time access.

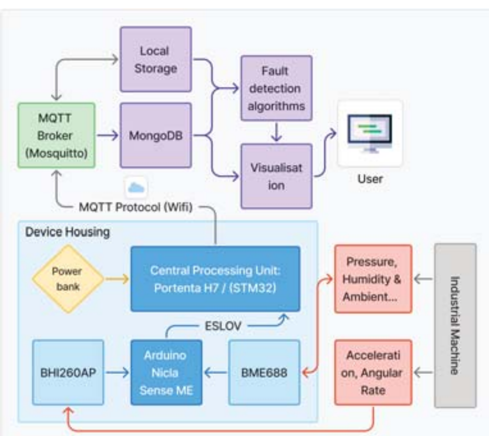

Fig. 1. System architecture of the embedded sensing device.

Fault detection algorithms operate on the stored sensor data, and their outputs are used for visualization and user interaction. This architecture enables continuous data acquisition on embedded hardware while decoupling sensing, communication, and analysis. The system is designed to reflect realistic deployment constraints and provides a flexible foundation for evaluating anomaly detection methods using embedded MEMS sensor data.

3.2. *Data collection*

The sensing architecture presented in the previous section was deployed on a mobile robotic platform to collect data under controlled yet realistic operating conditions over several days. Experiments were conducted under both normal operation and predefined abnormal wheel conditions, corresponding to manually introduced wheel defects. To ensure that the recorded signals accurately capture system dynamics and wheel-related behavior, careful attention was given to sensor placement, mechanical integration, and experimental repeatability. The sensors were mounted at a fixed location on the mobile robot, as shown in Fig. 2b, to minimize relative motion between the sensors and the chassis. This mounting strategy ensures that the measured motion and vibration signals accurately reflect platform dynamics and wheel-related behavior, while avoiding additional damping or resonance effects caused by loose or flexible attachments.

The dataset was recorded in a total of 140 repeated runs, with each run corresponding to

Fig. 2. Overview of the experimental setup and MEMS sensor with enclosure: (a) mobile robot operating in the test environment; (b) sensor mounting location on the robot and example accelerometer, gyroscope, and environmental sensor signals.

a complete operational cycle executed under a known wheel condition. All runs were executed using comparable trajectories and motion profiles to ensure consistency, while allowing natural variability arising from surface interaction and dynamic effects. Motion data were recorded at an output data rate of $250\,\mathrm{Hz}$, while environmental parameters were sampled at a lower rate of $1\,\mathrm{Hz}$ and temporally aligned during preprocessing.

The resulting dataset forms the basis for evaluating the proposed anomaly detection framework.

3.3. *Anomaly Detection Methodology*

Due to the combined effects of motion variability, surface interaction, and sensor noise, the resulting signals exhibit complex temporal patterns that are difficult to characterize using fixed, handcrafted features. Reliable discrimination between normal and faulty conditions therefore requires a data-driven approach capable of learning both short-term signal characteristics and longer-term temporal dependencies directly from the measured data. To address this requirement, an end-to-end deep learning approach is adopted, operating directly on raw sensor time-series windows. The anomaly detection task is formulated as a supervised classification problem, where each input segment is assigned to a corresponding wheel condition. This formulation enables the model to capture condition-specific temporal signatures while remaining robust to natural variability observed across experimental runs.

An MLSTM-FCN (Multivariate Long Short-Term Memory Fully Convolutional Network) Karim et al. (2019) architecture is employed to model the sensor time-series data. The convolutional branch captures local temporal patterns and inter-channel relationships, while the recurrent branch models longer-term temporal dependencies within each input window. The complementary representations learned by both branches are combined and used for classification, making the architecture well suited for multivariate sensor data with complex temporal structure.

The model is trained using supervised learning with categorical cross-entropy loss, and validation data are used to monitor generalization performance during training. Model selection is based on validation performance to avoid overfitting, ensuring that evaluation results reflect performance on previously unseen runs.

4. Experiments

In this case study, we define a delivery task for the mobile robots, in which the robot moves between multiple workstations. During task execution, time-series data from MEMS sensors are collected for subsequent model training. As illustrated in Fig. 3, several abnormal wheel conditions are considered, including missing wheels, worn wheels, stuck wheels, and damaged wheels. The proposed anomaly detector is trained to distinguish between normal and abnormal operating scenarios, thereby indicating when maintenance

Fig. 3. Different conditions of the wheels used to record the dataset.

intervention is required. The evaluation of the model's inference performance focuses on two aspects: overall classification capability and the contribution of individual model components assessed through ablation studies. As reference metrics, we adopt widely used evaluation measures for assessing the performance of the anomaly detector, including classification accuracy and the macro-averaged F1 score.

4.1. *Overall Performance*

First, the overall capability of the model to distinguish between normal and abnormal conditions is evaluated. The collected dataset is divided into training and testing subsets with a ratio of 70% to 30%. Table 1 reports the classification performance on the test set using all features. Overall, the proposed model demonstrates strong discriminative capability between normal and abnormal operating conditions, achieving a macro-averaged F1 score of 0.9322 and a weighted F1 score of 0.9458.

For the normal class, the model achieves the best recall (1.0000), indicating that all normal samples are correctly identified. This behavior is desirable in robotic systems, as it minimizes false alarms during regular operation. Although the precision for the normal class is slightly lower (0.8241), this trade-off reflects a conservative decision boundary that favors detecting abnormal conditions. In contrast, the abnormal class exhibits the best precision (1.0000) and high recall (0.9245), suggesting that detected anomalies are highly reliable while maintaining strong coverage of actual abnormal cases. The resulting F1 score of 0.9608 highlights the effectiveness of the proposed approach in identifying wheel-related abnormal scenarios.

Table 1. Classification report for the test set using all features and the argmax decision rule.

Class	Prec.	Rec.	F1	Support
Normal	0.8241	1.0000	0.9036	2901
Abnormal	1.0000	0.9245	0.9608	8199
Macro Avg	0.9121	0.9623	0.9322	11100
Weighted Avg	0.9540	0.9442	0.9458	11100

From a maintenance perspective, the high precision achieved for the abnormal class ensures that detected fault cases correspond to genuine wheel degradation, thereby reducing unnecessary maintenance actions and enabling more reliable condition-based maintenance scheduling.

4.2. *Ablation Study*

To assess the contribution of individual sensor modalities to classification performance, a feature-level ablation study was conducted. The input sensor channels were selectively modified, while the same MLSTM-FCN architecture was used for training. The results are shown in Fig. 4. Using all sensor features yields the best performance, achieving an accuracy of 94.42% and a macro-averaged F1 score of 93.22%, which confirms the benefit of multi-modal sensor fusion for wheel anomaly detection.

When restricting the input to accelerometer signals only, the model still maintains relatively strong performance, with an accuracy of 81.85% and a macro F1 score of 80.03%. In contrast, using gyroscope signals alone leads to a notable performance degradation, indicating that accelerometer measurements provide more discriminative information for the considered wheel-related anomalies.

A more detailed analysis of individual sensor

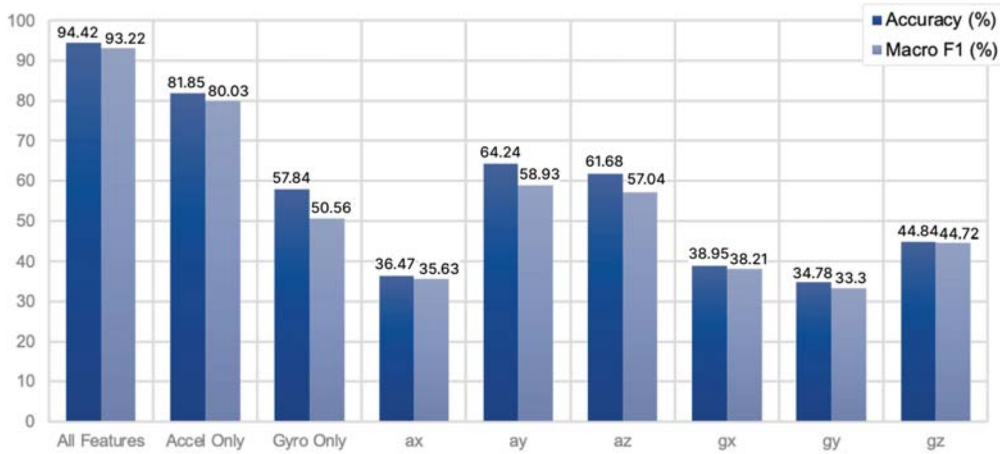

Fig. 4. Performance by input configuration

axes reveals that the lateral and vertical acceleration components (*ay* and *az*) contribute most significantly to classification performance, whereas single-axis gyroscope inputs result in substantially lower accuracy and F1 scores. This suggests that vibration patterns captured by specific acceleration directions are more sensitive to wheel degradation and abnormal contact conditions.

Overall, the results demonstrate that while acceptable performance can be achieved with reduced sensor configurations, combining multiple sensor modalities and axes substantially improves robustness and class separability. These findings are particularly relevant for embedded implementations, where performance–cost trade-offs must be considered when selecting sensor configurations.

5. Conclusion

This paper presented a deep learning–based anomaly detection framework for wheel condition monitoring using compact, MEMS-based sensor hardware. A microcontroller-driven sensing platform was deployed on a mobile robotic system to collect multi-modal motion data under realistic operating conditions, resulting in a labeled dataset comprising normal operation and multiple fault scenarios. An MLSTM-FCN architecture was trained directly on raw sensor time series, avoiding handcrafted feature design. Experimental results demonstrate that the proposed approach achieves high classification performance and robust separation between normal and abnormal operating conditions. Sensor-level ablation analysis shows that accelerometer signals provide the dominant fault information, while multi-axis sensing improves robustness and class-balanced performance. Signal-level analysis further reveals that abnormal conditions are characterized by intermittent, localized transient events, highlighting the suitability of end-to-end learning approaches for capturing non-stationary fault signatures. Overall, the results confirm the feasibility of combining MEMS-based sensing with deep learning for embedded condition monitoring and prognostics. Future work will focus on real-time deployment, online inference, and extending the framework to broader fault types and operational settings.

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