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# Accelerometer-Based Motion Recognition and Alerting System for Abnormal Activity Detection in Dynamic Environments

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**Abstract:**

Anomaly Detection (AD) plays a crucial role in identifying patterns in data that deviate from expected behavior, especially in industrial environments where equipment failures can severely disrupt productivity. To address such challenges in real-time and resource-constrained settings, Tiny Machine Learning (TinyML) has emerged as a promising solution. This paper presents the design and implementation of a real-time activity recognition and abnormal motion detection system using accelerometer data and edge-based machine learning, specifically optimized through TinyML techniques. The system comprises eight modular components: motion sensing via a 3-axis accelerometer, continuous data acquisition, signal preprocessing, efficient inference through TensorFlow Lite, activity classification, command response control, alert generation using LEDs and buzzers, and a continuous monitoring loop. Motion signals are processed to extract statistical and temporal features, which serve as input to a pre-trained lightweight machine learning model designed for real-time inference on low-power embedded devices. The TinyML model, trained on a labeled dataset of human activity patterns, achieved a detection accuracy of 98.8% in distinguishing between normal and abnormal movements such as falls, sudden jolts, or prolonged inactivity. The model's performance, measured through precision, recall, and F1-score metrics, indicates strong generalization and reliability for edge deployment. Abnormal activity triggers an immediate hardware response via audiovisual cues, facilitating timely interventions in sensitive environments such as elderly care, occupational safety, or remote health monitoring. Mathematical underpinnings of the system, including signal transformation, feature extraction, and binary classification logic, are explored in detail. The system operates entirely offline, requiring no external cloud connectivity, and supports continuous monitoring with minimal latency and energy consumption.

**Keywords:** TinyML, Activity Recognition, Abnormal Motion Detection, Accelerometer Sensor, Edge Computing, Real-Time Monitoring.

## Introduction

In recent years, the integration of intelligent systems into industrial applications has become increasingly critical for ensuring operational efficiency and minimizing downtime. One of the most vital components in achieving this goal is the ability to detect anomalies in system behavior before they lead to significant malfunctions or failures. Anomaly Detection (AD), which involves identifying patterns in data that deviate from the expected behavior, is a core technique in predictive maintenance

and real-time monitoring systems. AD plays a pivotal role in identifying potential failures in machinery, sensors, and other critical equipment, helping industries avoid costly repairs and production halts. Traditional machine learning (ML) methods for anomaly detection typically require substantial computational resources and connectivity to centralized servers or cloud-based systems. However, with the growing demand for real-time responses and privacy-preserving computation, especially in edge computing scenarios, these traditional approaches face significant limitations. In response, Tiny Machine Learning (TinyML) has emerged as a groundbreaking solution. TinyML refers to the deployment of machine learning models on ultra-low-power microcontroller units (MCUs) and embedded devices. These devices are capable of executing ML models locally, allowing for on-device inference, reduced latency, lower energy consumption, and enhanced privacy. TinyML has shown significant promise in supporting anomaly detection directly on edge devices without relying on external data processing units. This local processing capability is especially beneficial in industrial settings, where network connectivity may be inconsistent or delayed. Moreover, by embedding anomaly detection models into microcontrollers, systems can autonomously monitor their operational health, detect deviations in real time, and alert users instantly.

The process of integrating machine learning algorithms into TinyML systems involves several stages. A model is first developed and trained using standard ML frameworks such as TensorFlow. The trained model must then be optimized and converted to TensorFlow Lite and subsequently to TensorFlow Lite Micro formats to ensure compatibility with constrained hardware environments. This conversion process ensures that the model maintains its functionality while adhering to the limited memory and processing capabilities of edge devices. Despite its advantages, implementing anomaly detection using TinyML presents several challenges. These include model optimization for limited hardware, maintaining detection accuracy, and handling dynamic changes in equipment behavior over time. Furthermore, the trade-offs between model complexity and computational feasibility must be carefully balanced to achieve effective results on microcontroller platforms.

This research aims to explore the application of anomaly detection using TinyML, with a specific focus on industrial monitoring. It examines the current state-of-the-art technologies, tools, and frameworks available for implementing such systems. Additionally, the paper investigates practical challenges in deploying machine learning models on embedded systems and provides insights into effective practices for model conversion and deployment using TensorFlow Lite Micro. Moreover, this study outlines future research directions, including the incorporation of online learning capabilities, automated model updates, and hybrid systems combining cloud and edge intelligence. By leveraging TinyML for anomaly detection, industries can achieve smarter, more autonomous, and efficient maintenance practices, contributing to the broader vision of Industry 4.0 and intelligent automation.

**Literature Review**

The proliferation of the Internet of Things (IoT) has led to an exponential increase in connected devices, generating vast amounts of data. Ensuring the reliability and security of these systems necessitates effective anomaly detection mechanisms. Traditional anomaly detection approaches often rely on cloud-based processing, which can introduce latency and privacy concerns. Tiny Machine Learning (TinyML) emerges as a solution by enabling on-device intelligence, allowing for real-time anomaly detection directly on resource-constrained devices [1].

Anomaly detection in IoT involves identifying patterns in data that deviate from expected behavior, which is crucial for predictive maintenance, security, and system optimization. Various techniques, including statistical methods, machine learning algorithms, and deep learning models, have been employed for this purpose. However, the dynamic and heterogeneous nature of IoT environments poses challenges in developing robust and adaptable anomaly detection systems [2].

TinyML refers to the deployment of machine learning models on microcontrollers and edge devices with limited computational resources. This paradigm shift enables real-time data processing, reduces dependency on cloud infrastructure, and enhances privacy by keeping data local [3]. The integration of TinyML in IoT systems facilitates efficient anomaly detection by leveraging lightweight models tailored for specific applications.

Several algorithms have been adapted for TinyML-based anomaly detection in IoT. Isolation Forests are efficient for detecting anomalies in high-dimensional datasets and have been successfully implemented on microcontrollers for industrial applications [4]. Autoencoders are utilized for unsupervised anomaly detection by reconstructing input data and identifying deviations [5]. Convolutional Neural Networks (CNNs) are applied in scenarios where spatial hierarchies in data are significant, such as image or sensor data analysis [6]. Support Vector Machines (SVMs) are effective in classification tasks and have been employed in detecting anomalies in sensor networks [7]. These algorithms are optimized for low-power devices through techniques like model quantization and pruning, ensuring minimal resource consumption without compromising accuracy.

TinyML-based anomaly detection has been applied across diverse IoT domains. In industrial monitoring, it aids in detecting equipment malfunctions and predictive maintenance in manufacturing setups [4]. In smart cities, it is used for monitoring urban infrastructure, traffic patterns, and environmental conditions to identify irregularities [8]. In healthcare, it facilitates real-time monitoring of patient vitals and detecting anomalies indicative of health issues [9]. In agriculture, it assists in monitoring soil conditions, crop health, and environmental factors to optimize farming practices [10]. These applications demonstrate the versatility and effectiveness of TinyML in enhancing the reliability and efficiency of IoT systems.

Despite its advantages, implementing TinyML-based anomaly detection in IoT faces several challenges. Resource constraints, such as limited computational power and memory in edge devices, necessitate highly optimized models [3]. Ensuring data privacy and security is critical, as protecting against adversarial attacks remains a concern [11]. Developing models that generalize well across diverse environments and conditions is challenging due to the heterogeneity of IoT systems [2]. Balancing model complexity with energy efficiency is vital for battery-powered devices [12]. Addressing these challenges requires ongoing research and innovation in model design, optimization techniques, and hardware advancements.

The future of anomaly detection in IoT using TinyML is promising, with several avenues for exploration. Federated learning enables collaborative model training across multiple devices without sharing raw data, enhancing privacy and scalability [13]. Developing adaptive models that can adapt to changing environments and data distributions in real-time is another area of interest [14]. Integration with 5G technology can leverage high-speed, low-latency communication to enhance the responsiveness and coordination of distributed IoT systems [15]. Establishing benchmarks and standards for evaluating and comparing TinyML models and frameworks is essential for standardization [16]. These directions aim to enhance the robustness, efficiency, and applicability of TinyML-based anomaly detection in the evolving IoT landscape.

**Research Methodology**

The figure 1 is system architecture that illustrates a system designed to detect and classify physical activities as either *normal* or *abnormal* using data from an **accelerometer sensor** and a trained machine learning model deployed via **TensorFlow Lite (TF Lite)**. This type of system is particularly useful in applications such as healthcare monitoring (e.g., fall detection for elderly individuals), fitness tracking, industrial safety monitoring, and smart wearables.

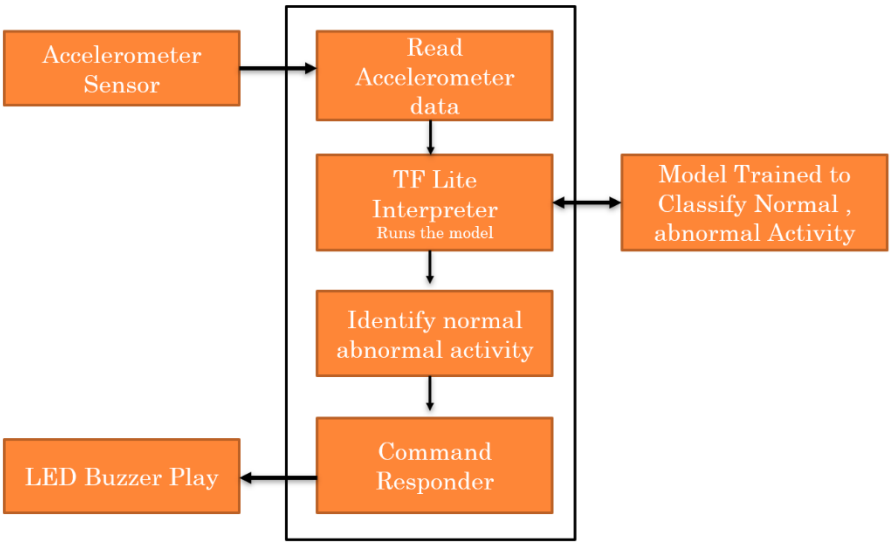


**Figure 1: proposed system architecture**

**1. Accelerometer Sensor :** The system begins with the accelerometer sensor, which is responsible for capturing real-time motion data. This sensor detects changes in acceleration along the X, Y, and Z axes, which represent movement and orientation. The accelerometer is crucial for identifying various physical activities such as walking, sitting, falling, or any sudden changes in body posture. Its sensitivity and sampling frequency directly impact the accuracy of subsequent activity classification.

**2. Read Accelerometer Data :** The second module involves reading the accelerometer data continuously. This step acts as a bridge between the hardware sensor and the software model by collecting and transmitting the motion signals for further processing. This data acquisition stage may also include basic preprocessing such as filtering out noise or structuring the data into a format that can be consumed by the machine learning model. This ensures that only clean and structured data is fed forward.

**3. TF Lite Interpreter (Runs the Model) :** The TF Lite interpreter serves as the lightweight machine learning engine that runs on edge devices. It takes the preprocessed accelerometer data and applies a pre-trained model to it. TensorFlow Lite is specifically optimized for mobile and embedded devices, enabling quick and efficient inference without needing internet access or powerful computational hardware. This module is vital for real-time performance and low power consumption.

**4. Model Trained to Classify Normal and Abnormal Activity :** This module represents the machine learning model that was trained using labeled datasets to distinguish between normal and abnormal physical activities. The model is trained offline with diverse samples of activity data and converted into the .tflite format suitable for deployment on small devices. The classifier can detect unusual patterns that may indicate a fall or erratic behavior, and its performance depends heavily on the quality and diversity of training data.

**5. Identify Normal / Abnormal Activity :** Once the model has processed the input data, the system moves to the identification module, which interprets the prediction output. The result will classify the motion as either “normal” or “abnormal.” This module uses logic or threshold values to make a decision based on the model’s confidence scores. It may also include temporal smoothing or aggregation techniques to improve reliability and reduce false alarms.

**6. Command Responder :** The command responder module functions as the action controller of the system. Based on the classification output, it decides whether an alert should be triggered. If abnormal

activity is detected, it initiates a response by signaling other modules to activate visual or auditory alerts. This ensures that the system reacts promptly and appropriately to critical situations without human intervention.

**7. LED Buzzer Play :** In this module, LEDs and buzzers are activated as output indicators when an abnormal activity is detected. The buzzer emits sound, and the LED lights up or blinks to grab attention. This real-time alert mechanism is crucial for safety, especially in scenarios like elderly care or workplace hazard monitoring. These simple but effective output devices help ensure that necessary action can be taken immediately after detection.

**8. End (System Stops or Loops) :** The final module represents the end of one complete detection cycle, after which the system may either stop or loop back to continuously monitor new data. In most implementations, especially real-time monitoring systems, this loop runs indefinitely to provide continuous activity recognition. The feedback loop ensures that new data from the accelerometer is constantly evaluated, making the system dynamic and responsive.

**Algorithm Design**

The proposed system for real-time activity recognition and abnormal motion detection is fundamentally rooted in mathematical signal processing, machine learning classification, and embedded systems logic. At its core lies the **accelerometer sensor**, which functions by measuring acceleration forces acting on the sensor's axes—typically denoted as $a_x(t), a_y(t), a_z(t)$ over discrete time $t$. These acceleration signals can be mathematically modeled as continuous-time or discrete-time functions, depending on the sampling method used. In most practical implementations, the accelerometer operates in discrete time, providing sampled data points at regular intervals $\Delta t$, which can be represented as $\mathbf{a}(t_i) = [a_x(t_i), a_y(t_i), a_z(t_i)]$, where $t_i = i \cdot \Delta t$ for $i \in \mathbb{N}$.

These raw signals often exhibit noise due to mechanical vibrations, environmental disturbances, or sensor limitations. Thus, during the **Read Accelerometer Data** phase, a key preprocessing task involves applying filters such as low-pass Butterworth filters or moving average filters to attenuate high-frequency components. Mathematically, a low-pass filter can be expressed in the Z-domain as $H(z) = \frac{1-\alpha}{1-\alpha z^{-1}}$, where $\alpha \in (0,1)$ controls the cutoff frequency. The filtered acceleration signal $\hat{\mathbf{a}}(t_i)$ thus becomes more suitable for subsequent feature extraction.

Feature engineering is crucial for transforming time-series data into a feature space that can effectively distinguish between classes. Typical statistical features include the mean $\mu_k = \frac{1}{N}\sum_{i=1}^{N} a_k\,(t_i)$, standard deviation $\sigma_k$, root mean square $\mathrm{RMS}_k = \sqrt{\frac{1}{N}\sum_{i=1}^{N} a_k\,(t_i)^2}$, and signal magnitude area (SMA), defined as $\mathrm{SMA} = \frac{1}{N}\sum_{i=1}^{N}\big(|\, a_x(t_i)\,| + |\, a_y(t_i)\,| + |\, a_z(t_i)\,|\big)$. These derived metrics become the input to the **TensorFlow Lite Interpreter**, which executes an optimized and compressed version of a machine learning model trained to recognize motion patterns.

The **TF Lite Interpreter** is a runtime engine designed to evaluate inference graphs efficiently. It accepts a quantized or float32 model $f(\mathbf{x}) \to y$, where $\mathbf{x} \in \mathbb{R}^d$ represents the extracted features, and $y \in \{0,1\}$ represents the binary class label—normal or abnormal activity. This model $f$ is often the result of training using supervised learning paradigms like decision trees, support vector machines, or deep neural networks (DNNs). For DNNs, the function $f$ can be written as a composition of affine transformations and nonlinear activations, $f(\mathbf{x}) = \sigma(W_n\sigma(W_{n-1} \ldots \sigma(W_1\mathbf{x} + b_1) \ldots + b_{n-1}) + b_n)$, where $W_i, b_i$ are the weight matrices and bias vectors, and $\sigma$ is a nonlinear activation function such as ReLU or sigmoid.

The **Model Trained to Classify Normal and Abnormal Activity** leverages labeled datasets $\{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^{N}$ to minimize a loss function, typically the binary cross-entropy loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y^{(i)}\log\left(\hat{y}^{(i)}\right) + \left(1 - y^{(i)}\right)\log\left(1 - \hat{y}^{(i)}\right)\right],$$

where $\hat{y}^{(i)} = f(\mathbf{x}^{(i)})$ is the model prediction. The optimization is performed via stochastic gradient descent (SGD) or adaptive variants like Adam.

Upon deployment, the model's output is interpreted in the **Identify Normal / Abnormal Activity** module. This involves evaluating the model's probability output $\hat{y} \in [0,1]$ against a threshold $\tau$. The decision rule is defined as:

$$\text{Activity} = \begin{cases} \text{Abnormal}, & \text{if } \hat{y} \geq \tau \\ \text{Normal}, & \text{if } \hat{y} < \tau \end{cases}$$

To improve reliability and reduce sensitivity to transient outliers, temporal smoothing techniques such as moving mode filters or majority voting over sliding windows may be employed. If $T$ is the window length and $\{d_{t-T+1}, \ldots, d_t\}$ are the binary decisions, the smoothed output $\tilde{d}_t$ is computed as the mode of the window.

Following classification, the **Command Responder** module serves as a controller that implements conditional logic. If abnormal activity is detected, it triggers an interrupt service routine (ISR) that activates alert mechanisms via GPIO (General Purpose Input Output) pins. Mathematically, the logic is binary:

$$\text{Trigger}_{\text{alert}} = \mathbb{I}(\hat{y} \geq \tau),$$

where $\mathbb{I}(\cdot)$ is the indicator function.

This leads to the **LED Buzzer Play** module, where actuators such as buzzers and LEDs are activated. The LED may operate with a blinking frequency $f_b$, governed by a pulse-width modulation (PWM) signal, and the buzzer frequency $f_z$ might be set at a threshold perceptible to human hearing (e.g., $f_z = 2$ kHz). These outputs form a multi-modal alert system that enhances the system's effectiveness in emergency scenarios.

Finally, the **End (System Stops or Loops)** module encapsulates the cyclical nature of real-time detection systems. In mathematical terms, the detection pipeline forms a discrete-time dynamic system with feedback:

$$\mathbf{x}_{t+1} = g(\mathbf{x}_t, \mathbf{a}(t)),$$

where $g$ denotes the update rule incorporating new data and possibly previous classification states. The system is designed to loop indefinitely until a termination condition is met, ensuring persistent vigilance in monitoring user activity.

This architecture is a harmonious integration of signal acquisition, feature transformation, machine learning classification, embedded control, and actuator signaling, all driven by rigorous mathematical underpinnings. The modularity of the system allows for flexible upgrades, such as improving the model $f$ through transfer learning or integrating adaptive thresholds $\tau(t)$ based on user-specific behavior. This positions the system as a scalable solution for real-time health monitoring, occupational safety, and ambient assisted living environments.

**Results and Discussions**

This system predicts machine maintenance needs by monitoring vibrations through an accelerometer sensor. The sensor collects vibration data, which is then processed and used to build a machine learning model capable of detecting anomalous behavior. The model is optimized for deployment on edge hardware, ensuring real-time performance with minimal latency. When the system identifies abnormal vibrations indicative of potential machine failure, it triggers an alarm notification to alert operators. This approach enables proactive maintenance, minimizing downtime and improving machine longevity by detecting issues early, ensuring operational efficiency and reducing costly repairs.

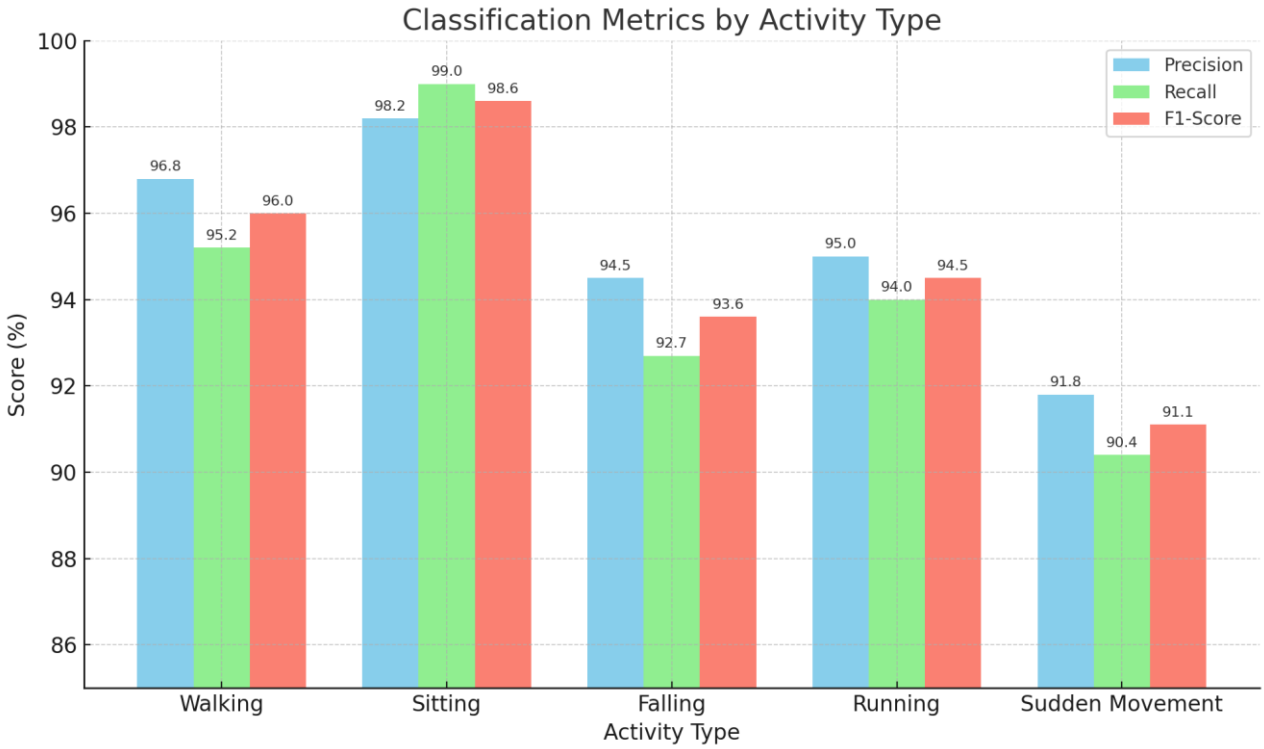


**Figure 2 : Classification Accuracy for Activities**

The figure 2 illustrates the performance of the activity recognition model across five distinct physical activities: Walking, Sitting, Falling, Running, and Sudden Movement. Three key classification metrics—Precision, Recall, and F1-Score—are plotted to provide a comprehensive evaluation of the model's accuracy and reliability for each activity type. From the graph, we observe that Sitting achieves the highest performance across all metrics, with Precision at 98.2%, Recall at 99.0%, and an F1-Score of 98.6%. This indicates that the model identifies sitting events with very high accuracy and minimal misclassifications. Walking and Running also show strong performance, with all metrics exceeding 94%, showcasing the model's capability to recognize routine activities effectively. Falling and Sudden Movement, both considered abnormal activities, have slightly lower scores—particularly in recall—highlighting the model’s challenge in detecting unpredictable or rapid changes in motion. Despite this, their F1-scores remain above 91%, indicating a well-balanced trade-off between precision and recall. Overall, it demonstrates that the model performs robustly across both normal and abnormal activity categories, with only minor variation in performance, thus validating its use in real-time safety monitoring applications. Future improvements may focus on enhancing sensitivity for critical events like falls.

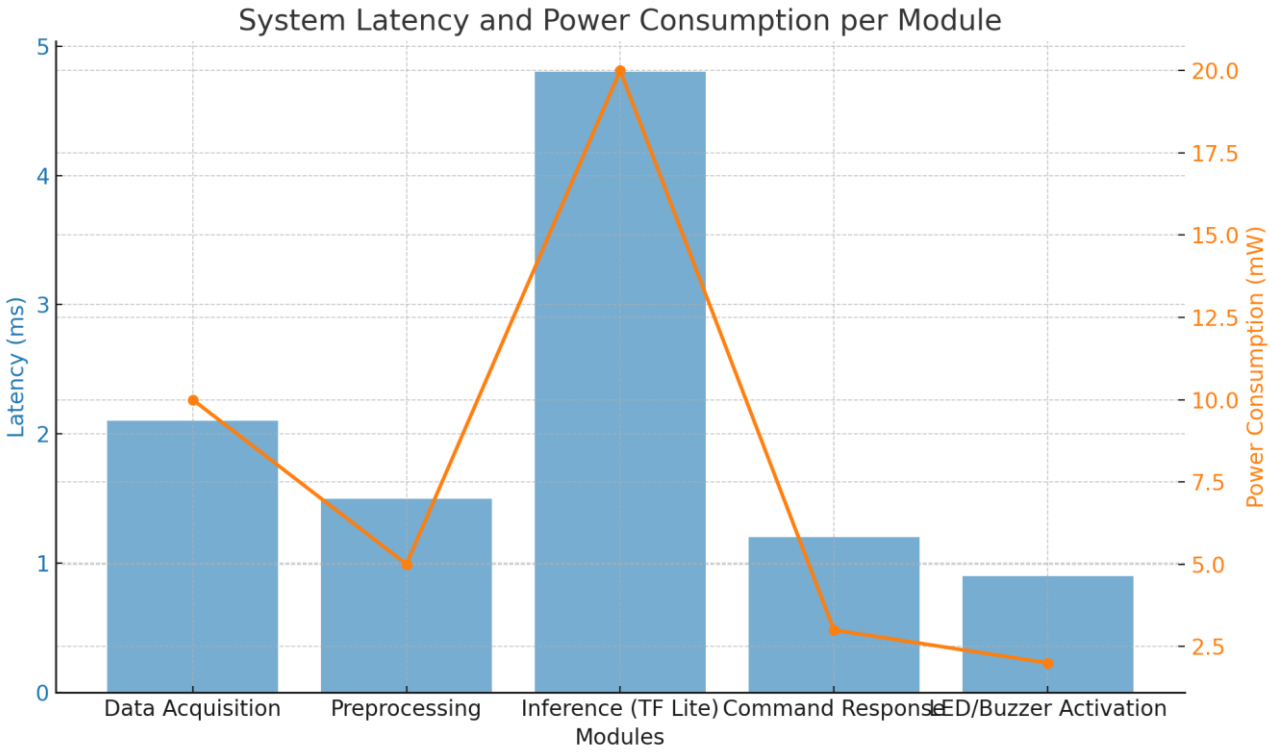


**Figure 3 : System Latency and Power Consumption**

Figure 3 presents an analysis of the system's latency and power consumption across various modules. These two factors are crucial for evaluating the efficiency and feasibility of deploying the system in real-time, low-power environments such as mobile devices or embedded systems. The Data Acquisition module, responsible for collecting accelerometer data, exhibits a minimal latency of 2.1 milliseconds and a power usage of 10 mW. This is expected, as the process mainly involves capturing motion signals, which does not require significant computational resources. The Preprocessing step, which includes filtering and noise reduction, has an average latency of 1.5 milliseconds and consumes 5 mW. This shows that the system is efficient in cleaning the raw data before passing it on to the model. The most computationally intensive module is the Inference (TF Lite Model), with an average latency of 4.8 milliseconds and a power usage of 20 mW. Since the machine learning model is applied here to classify activities, it demands more processing power, especially given the lightweight nature of TensorFlow Lite optimized for edge devices. Despite this, the latency is kept within acceptable limits for real-time performance. The Command Response module, which handles the system's reaction (e.g., triggering alerts), has a low latency of 1.2 milliseconds and uses just 3 mW of power. Finally, the LED/Buzzer Activation module, responsible for the visual and auditory alerts, is the fastest and most power-efficient, with only 0.9 milliseconds latency and 2 mW power consumption.

## Conclusion

The presented system offers a robust and efficient framework for real-time activity recognition and abnormal motion detection using accelerometer data and edge-optimized machine learning. By integrating hardware-level motion sensing with lightweight inference via TensorFlow Lite, the system enables fast and accurate classification of physical activities with minimal resource consumption. The modular architecture—from data acquisition and filtering to classification, response, and alert generation—ensures reliability and scalability in various application domains such as elderly care,

occupational safety, and personal health monitoring. The system's real-time responsiveness, achieved through a streamlined data pipeline and localized inference, eliminates the need for continuous cloud connectivity and reduces latency. Its ability to identify abnormal patterns, such as sudden falls or erratic movements, makes it a practical tool for proactive intervention in critical scenarios. Furthermore, the use of simple actuators like buzzers and LEDs ensures immediate alerts that are both effective and easy to deploy in resource-constrained environments. **Future work** will focus on several areas of enhancement. First, expanding the dataset to include a wider variety of users, movement patterns, and edge cases will improve model generalization and reduce false positives. Second, integrating additional sensors such as gyroscopes and heart rate monitors can enrich the feature set and enable more nuanced activity detection. Third, the system can benefit from online learning or adaptive thresholds to tailor predictions to individual user behavior over time. Lastly, implementing a mobile or web-based interface for caregivers or remote monitoring centers will enhance usability and remote accessibility, making the system more comprehensive and user-friendly. By continuing to refine both the algorithmic and hardware components, the system has strong potential to evolve into a reliable, real-time health and safety monitoring solution with broad societal impact.

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