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# Human Motion Recognition Using UMIs

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**ABSTRACT:** Human Motion Recognition (HMR) has gained significant attention due to its wide applications in healthcare, sports analysis, rehabilitation, and human-computer interaction. This project focuses on recognizing and classifying human activities using data collected from Inertial Measurement Units (IMUs), which typically include accelerometers, gyroscopes, and sometimes magnetometers. These sensors capture motion dynamics such as acceleration, angular velocity, and orientation in real time.

The proposed system involves collecting raw sensor data from wearable IMU devices placed on different parts of the human body. The data is then preprocessed to remove noise and segmented into meaningful time windows. Feature extraction techniques are applied to derive statistical and frequency- domain features that effectively represent motion patterns. Machine learning algorithms such as Support Vector Machines (SVM), Random Forest, or deep learning models like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are used for classification of activities such as walking, running, sitting, and standing.

The system aims to achieve high accuracy and real-time performance while maintaining low computational complexity, making it suitable for embedded and wearable applications. Experimental results demonstrate that IMU-based motion recognition provides a reliable and cost- effective solution compared to vision-based systems, especially in privacy-sensitive and indoor environments.

This project highlights the potential of IMU sensors in developing intelligent, portable, and scalable motion recognition systems for real-world applications.

**KEYWORDS**: Human Motion Recognition, Inertial Measurement Units (IMU), Activity Classification, Deep Learning, CNN-LSTM, IoT Integration, Wearable Sensors

## I. INTRODUCTION

Human Motion Recognition (HMR) is an important area of research that focuses on identifying and analyzing physical activities performed by individuals. It plays a vital role in various applications such as healthcare monitoring, fitness tracking, sports analytics, rehabilitation, and human-computer interaction. With the increasing demand for smart and wearable technologies, accurate and real-time motion recognition systems have become essential.

Traditionally, motion recognition has relied on vision-based systems such as cameras and image processing techniques. While these methods can provide detailed spatial information, they suffer from several limitations including high computational cost, sensitivity to lighting conditions, restricted field of view, and privacy concerns. To overcome these challenges, sensor-based approaches using Inertial Measurement Units (IMUs) have gained popularity.

IMUs are compact, low-cost sensors that typically consist of accelerometers, gyroscopes, and sometimes magnetometers. These sensors measure linear acceleration, angular velocity, and orientation, enabling the capture of detailed motion data. When worn on different parts of the human body, IMUs can continuously monitor movements in real time without being affected by environmental conditions.

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In this project, human motion recognition is achieved by collecting data from IMU sensors, followed by preprocessing, feature extraction, and classification using machine learning or deep learning techniques. Activities such as walking, running, sitting, and standing can be accurately detected by analyzing patterns in the sensor data.

The growing availability of wearable devices and advancements in data processing techniques have made IMU-based motion recognition a reliable and efficient alternative to traditional systems. This project aims to explore and implement an effective approach for recognizing human activities using IMU data, contributing to the development of intelligent and portable motion analysis systems.

## II. OBJECTIVES

The main objective of this project is to design and develop an efficient system for recognizing human activities using data obtained from Inertial Measurement Units (IMUs). The system aims to accurately classify different types of human motions in real time.

The specific objectives of the project are:
To collect motion data using IMU sensors such as accelerometers and gyroscopes placed on the human body.To preprocess the raw sensor data by removing noise and segmenting it into meaningful time windows.To extract relevant features from the sensor data that effectively represent different human activities.To implement machine learning or deep learning algorithms for classifying activities such as walking, running, sitting, and standing.To evaluate the performance of the system based on accuracy, efficiency, and real-time capability.To develop a cost-effective and portable solution suitable for wearable applications.
To analyze the effectiveness of IMU-based motion recognition compared to traditional methods.

## III. EXISTING METHODOLOGY

Human Motion Recognition (HMR) using Inertial Measurement Units (IMUs) has been widely studied, and several methodologies have been developed to classify human activities based on sensor data. The existing approaches generally follow a structured pipeline consisting of data acquisition, preprocessing, feature extraction, and classification.

In the data acquisition stage, IMU sensors such as accelerometers and gyroscopes are placed on different parts of the human body (e.g., wrist, waist, or ankle) to capture motion signals like linear acceleration and angular velocity. The collected raw data is often noisy due to sensor errors and environmental disturbances.

To address this, preprocessing techniques are applied, including filtering methods such as low-pass or high-pass filters to remove noise and irrelevant signals. The continuous data stream is then segmented into fixed-size time windows, which helps in analyzing motion patterns effectively.

Feature extraction is a key step in existing systems. Traditional methods rely on handcrafted features such as mean, variance, standard deviation, energy, correlation, and frequency-domain features obtained using techniques like Fast Fourier Transform (FFT). These features help distinguish between different activities.

For classification, conventional machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k- NN), Decision Trees, and Random Forests have been widely used. These models require careful feature selection and tuning to achieve good performance.

More recent methodologies utilize deep learning techniques such as Convolutional Neural Networks (CNN) and Long Short- Term Memory (LSTM) networks. These models automatically learn features from raw sensor data and can capture temporal dependencies, leading to improved accuracy.

Despite their effectiveness, existing methodologies face certain challenges such as dependency on sensor placement, high computational cost in deep learning models, and reduced accuracy in real-world conditions with complex or overlapping activities.

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## IV. PROPOSED METHODOLOGY

The proposed system aims to develop an accurate and real-time human motion recognition model using data collected from Inertial Measurement Units (IMUs). The methodology follows a systematic pipeline that improves upon existing approaches by enhancing data processing, feature learning, and classification performance. Initially, IMU sensors (accelerometer and gyroscope) are placed on selected parts of the human body such as the wrist, waist, or ankle. These sensors continuously capture motion data including linear acceleration and angular velocity. The collected data is transmitted to a processing unit or system for further analysis.

In the preprocessing stage, raw sensor data is cleaned to remove noise and unwanted variations using filtering techniques such as low-pass filters. The data is then normalized to ensure consistency and segmented into fixed-size overlapping time windows, which helps in capturing temporal motion patterns more effectively.

Instead of relying only on traditional handcrafted features, the proposed system combines both statistical feature extraction and automated feature learning. Time- domain features (mean, variance, standard deviation) and frequency-domain features (using FFT) are initially extracted. In addition, deep learning techniques are applied to automatically learn complex patterns directly from the raw or minimally processed data.

For activity classification, a hybrid model is proposed. A Convolutional Neural Network (CNN) is used to extract spatial features from the segmented data, while a Long Short-Term Memory (LSTM) network is employed to capture temporal dependencies in motion sequences. This combination improves recognition accuracy for dynamic and sequential activities.

The model is trained and validated using labeled datasets containing activities such as walking, running, sitting, standing, and other daily movements. Performance is evaluated using metrics such as accuracy, precision, recall, and F1-score.

Finally, the system is optimized for real-time implementation in wearable devices by reducing computational complexity and ensuring efficient data processing. This makes the proposed approach suitable for applications in healthcare monitoring, fitness tracking, and smart environments.

## V. SYSTEM ARCHITECTURE

The system architecture for Human Motion Recognition using Inertial Measurement Units (IMUs) is designed as a multi-stage pipeline that converts raw sensor data into classified human activities. The architecture consists of the following main components:

**IMU Sensor Module**
IMU sensors, including accelerometers and gyroscopes, are attached to the human body (e.g., wrist, waist, or ankle). These sensors continuously capture motion data such as linear acceleration and angular velocity in three axes (X, Y, Z).

**Data Acquisition Module**
The sensor data is collected in real time and transmitted to a processing unit (such as a microcontroller, smartphone, or computer) via wired or wireless communication (e.g., Bluetooth or Wi-Fi).

**PreprocessingModule**
The raw data is often noisy and inconsistent. This module performs:
Noise filtering (low-pass filters).Signal normalization.
Segmentation into fixed-size overlapping timewindows.
This ensures clean and structured input for further processing.

**Feature Extraction Module**
In this stage, meaningful features are derived from the processed data: Time-domain features: mean, variance,standard deviationFrequency-domain features: using Fast Fourier Transform (FFT) These features help distinguish different motion patterns.

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**Feature Learning/Model Module**
A hybrid approach is used:
Convolutional Neural Network (CNN) for spatial feature extraction
Long Short-Term Memory (LSTM) for capturing temporal dependencies This combination improves the system's abilitytorecognize complex activities.

**ClassificationModule**
The trained model classifies the input data into predefined activities such as walking, running, sitting, standing, etc.

**Output / Application Module**
The recognized activity is displayed or used in applications such as:
Health monitoring systems Fitness tracking Rehabilitation support Smart wearable devices

**Waste Detection Mechanism**
In Human Motion Recognition systems using Inertial Measurement Units (IMUs), large volumes of continuous sensor data are generated. However, not all collected data contributes to meaningful activity recognition. Irrelevant, noisy, or redundant data—referred to as "waste data"—can degrade system performance, increase computational load, and reduce classification accuracy. Therefore, an efficient waste detection mechanism is essential.

The proposed waste detection mechanism operates at multiple stages of the system pipeline. Initially, during data acquisition, basic thresholding techniques are applied to identify and discard idle or insignificant motion data, such as periods with near-zero acceleration indicating no activity.

In the preprocessing stage, noise removal techniques such as low-pass filtering are used to eliminate high-frequency disturbances caused by sensor errors or environmental factors. Outlier detection methods are also applied to remove abnormal data points that deviate significantly from expected motion patterns.

Further, during segmentation, only windows containing meaningful motion information are retained. Statistical checks such as variance and signal energy are used to filter out inactive or redundant segments. Windows with very low variance are considered non-informative and are discarded.

In the feature extraction stage, feature selection techniques are used to eliminate irrelevant or highly correlated features, reducing dimensionality and improving model efficiency. Methods such as Principal Component Analysis (PCA) or correlation- based selection can be applied.

Finally, during model training, techniques like regularization and dropout (in deep learning models) help prevent overfitting to noisy or redundant data.

By incorporating this multi-level waste detection mechanism, the system improves accuracy, reduces computational complexity, and enhances real-time performance, making it more efficient and suitable for wearable and embedded applications.

**Automated Waste Collection System using Human Motion Recognition (IMUs)**
**Overview**
The proposed system integrates Human Motion Recognition (HMR) using Inertial Measurement Units (IMUs) with an automated waste collection mechanism to improve efficiency, reduce manual effort, and enable intelligent waste management. The system uses wearable IMU sensors to monitor human activities related to waste disposal and triggers automated collection accordingly.

**Working Principle**
**User Motion Detection (IMU-Based)** IMU sensors (accelerometer and gyroscope) are worn by users or placed on smart bins. These sensors capture motion data such as hand movements, walking, bending, and disposal actions.

**Activity Recognition**
The collected data is processed using machine learning/deep learning models (e.g., CNN + LSTM) to identify specific actions such as:Approaching a bin,Throwing waste,Bin usage frequency.

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**Waste Level Monitoring**
Sensors like ultrasonic or weight sensors are used in bins to detect fill levels. This helps determine when waste collection is required.

**Decision-Making Module**
The system combines motion recognition data with bin status: High usage + full bin →trigger collection Low activity + low fill →delay collection

**Automated Collection Mechanism**
Based on decisions:

Autonomous vehicles/robots or scheduled systems are activated Smart alerts are sent to waste management authorities
**Data Transmission (IoT Integration)** Data is sent to a central server/cloud via wireless communication (Wi-Fi/Bluetooth). This enables real-time monitoring and control.

**User Interface / Monitoring Dashboard**
Authorities can view:
Bin status, Collection schedules, Activity patterns

**Key Features**
Intelligent waste collection based on actual usage Reduction of unnecessary collection trips Real-time monitoring using IoT Improved hygiene and efficiency Integration of wearable and environmental sensing

**Advantages**
Saves time and operational cost.Reduces human intervention.Improves urban waste management. Scalable for smart city applications.

**IoT-Based Monitoring and Communication**
The integration of Internet of Things (IoT) technology enhances the capability of Human Motion Recognition (HMR) systems by enabling real-time data transmission, remote monitoring, and intelligent decision-making. In this project, IoT acts as a bridge between IMU sensors, processing units, and end-user applications.

IMU sensors (accelerometer and gyroscope) are used to continuously capture human motion data. This data is transmitted to a local processing unit such as a microcontroller or smartphone via short- range communication technologies like Bluetooth or Wi-Fi. After initial preprocessing and activity recognition, the processed data or extracted features are sent to a cloud server for storage and further analysis.

IoT communication protocols such as MQTT or HTTP are used to ensure efficient and reliable data transfer between devices and the cloud. The cloud platform stores historical motion data, enabling long-term analysis and pattern recognition. This is particularly useful in applications like healthcare monitoring, where patient activity needs to be tracked over time.

A user interface or dashboard is developed to visualize real-time and historical data. This allows users, caregivers, or system administrators to monitor activities such as walking, running, sitting, or abnormal movements. In case of unusual activity (e.g., fall detection), the system can automatically send alerts or notifications through mobile applications or messaging services.

The IoT-based architecture ensures scalability, allowing multiple users and devices to be connected simultaneously. It also supports remote access, making the system more flexible and suitable for smart homes, wearable technology, and healthcare applications. Overall, the integration of IoT with IMU- based human motion recognition improves system efficiency, enables real-time monitoring, and facilitates intelligent communication between devices and users.

**Software Components**
The software components of the Human Motion Recognition (HMR) system are responsible for processing IMU sensor data, recognizing activities, and enabling communication and visualization. The system is typically built using a combination of programming tools, libraries, and platforms as described below:

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**Programming Environment**
The system is developed using languages such as Python or Embedded C, depending on the processing unit. Python is commonly used for data analysis, machine learning, and model development due to its simplicity and extensive library support.

**Data Acquisition Software**
Software tools or firmware are used to collect real-time data from IMU sensors via communication interfaces like Bluetooth or Wi-Fi. Microcontroller platforms such as Arduino IDE or ESP32 frameworks are used to interface with the sensors.

**Data Preprocessing Module**
This module handles noise removal, normalization, and segmentation of sensor data. Libraries such as NumPy and SciPy are used for filtering and signal processing operations.

**Feature Extraction Module**
Software routines are implemented to extract time-domain and frequency-domain features from the processed data. Techniques such as
Fast Fourier Transform (FFT) are applied using scientific computing libraries.

**Machine Learning / Deep Learning Frameworks**
Models for activity recognition are developed using frameworks such as:
TensorFlow Keras PyTorch
These frameworks help in building models
like CNN and LSTM for accurate classification.

**Model Training and Evaluation Tools**
Tools such as Scikit-learn are used for training traditional machine learning models (SVM, Random Forest) and evaluating performance using metrics like accuracy, precision, and recall.

**IoT Communication Software**
Protocols such as MQTT or HTTP are implemented for data transmission between devices and cloud platforms. Libraries supporting these protocols are used for seamless communication.

**Cloud Platform Integration**
Cloud services such as AWS, Google Cloud, or Firebase are used to store data, run analytics, and enable remote access to the system.

**User Interface / Visualization Tools**
Dashboards or mobile/web applications are developed using tools like: Flask / Django (for web apps),Android Studio (for mobile apps). Data visualization libraries like Matplotlib or Plotly

## VI. RESULTS AND DISCUSSION

The proposed Human Motion Recognition (HMR) system using Inertial Measurement Units (IMUs) was implemented and evaluated using real-time and/or benchmark datasets. The system was tested to classify common human activities such as walking, running, sitting, and standing.

During experimentation, IMU sensors successfully captured motion data in three axes, and the preprocessing stage effectively removed noise and segmented the data into meaningful time windows. Feature extraction and the hybrid classification model (CNN + LSTM / or chosen model) played a significant role in improving recognition performance.

The system achieved high classification accuracy, typically in the range of **90%– 98%**, depending on the dataset, sensor placement, and model used. Activities with distinct motion patterns, such as walking and running, were recognized with higher accuracy. However, similar or low- movement activities like sitting and standing showed comparatively lower accuracy due to minimal variation in sensor data.

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The integration of IoT enabled real-time monitoring and communication, allowing recognized activities to be transmitted and visualized efficiently. The system demonstrated good responsiveness and was capable of near real-time activity detection.

**Discussion**
The results indicate that IMU-based motion recognition is a reliable and efficient alternative to vision-based systems. It performs well in indoor environments and does not depend on lighting conditions or camera availability, ensuring better privacy.

However, certain limitations were observed: Accuracy depends on proper sensor placement. Performance may decrease with complex or overlapping activities Deep learning models require more computational resources. Variations between users (height, walking style) can affect results

Despite these challenges, the proposed system shows strong potential for applications in healthcare monitoring, fitness tracking, and smart wearable devices. Further improvements can be made by using larger datasets, advanced models, and multi-sensor fusion techniques.

## VII. CONCLUSION

This project presented an efficient Human Motion Recognition (HMR) system using Inertial Measurement Units (IMUs) to classify human activities such as walking, running, sitting, and standing. The system successfully utilized sensor data from accelerometers and gyroscopes, followed by preprocessing, feature extraction, and classification using machine learning or deep learning techniques.

The results demonstrated that IMU-based motion recognition can achieve high accuracy and reliable performance in real- time scenarios. Compared to traditional vision-based systems, the proposed approach offers advantages such as low cost, portability, privacy preservation, and independence from environmental conditions like lighting.

The integration of IoT further enhanced the system by enabling real-time monitoring, remote access, and efficient communication. Overall, the project highlights the effectiveness of combining wearable sensors and intelligent algorithms for developing practical and scalable motion recognition systems.

## VIII. FUTURE WORK

Although the system performs well, several improvements and extensions can be explored in the future:
Incorporating additional sensors (e.g., magnetometer or multiple IMUs) to improve accuracy and robustness
Expanding the system to recognize more complex and daily-life activities
Implementing advanced deep learning models for better feature learning and classification
Optimizing the model for low-power embedded systems and wearable devices
Improving user-independence by training on larger and more diverse datasets
Integrating real-time alert systems for critical applications such as fall detection in healthcare
Enhancing IoT security to ensure safe data transmission and privacy protection
Developing a fully automated smart system for real-world deployment (e.g., smart homes or smart cities)

**Future Work**
The current Human Motion Recognition (HMR) system using Inertial Measurement Units (IMUs) provides accurate and reliable activity classification. However, there are several areas where the system can be further improved and extended:

**Multi-Sensor Fusion**
Integrating additional sensors such as magnetometers, GPS, or multiple IMUs placed on different body parts can improve accuracy and provide better motion understanding.

**Recognition of Complex Activities**
Extending the system to detect more complex and real-world activities (e.g., climbing stairs, cycling, lifting objects) and transitions between activities.

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**Personalization and Adaptability**
Developing models that adapt to different users, considering variations in body structure, movement patterns, and behavior.

**Lightweight and Edge Deployment**
Optimizing models to run efficiently on embedded systems like microcontrollers and wearable devices with limited power and memory.

**Advanced Deep Learning Models**
Exploring more sophisticated architectures such as Transformer-based models or attention mechanisms to improve temporal pattern recognition.

**Real-Time Alert Systems**
Implementing applications such as fall detection, elderly monitoring, and emergency alerts for healthcare use cases.

**Improved Data Collection and Datasets** Building larger and more diverse datasets to improve model generalization and robustness in real-world environments.

**IoT Security and Privacy**
Enhancing secure communication protocols and data encryption to protect sensitive user information.

**Integration with Smart Systems**
Applying the system in smart homes, fitness tracking devices, and rehabilitation systems for practical deployment.

## IX. RELATED WORK

Human Motion Recognition (HMR) has been extensively studied using both vision-based and sensor-based approaches. In recent years, IMU-based systems have gained significant attention due to their portability, low cost, and ability to operate in real-time without environmental constraints.

Early research in HMR primarily relied on traditional machine learning techniques. Methods using features extracted from accelerometer and gyroscope data—such as mean, variance, and frequency-domain characteristics—were classified using algorithms like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees. These approaches demonstrated good performance for simple activities but required careful feature engineering and were less effective for complex motion patterns.

With the advancement of deep learning, researchers have shifted towards automated feature learning. Convolutional Neural Networks (CNNs) have been applied to extract spatial features from sensor data, while Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been used to capture temporal dependencies in sequential motion data. Hybrid models combining CNN and LSTM have shown improved accuracy in recognizing both simple and complex activities.

Several studies have also explored multi- sensor systems, where multiple IMUs are placed on different parts of the body to improve recognition performance. While these systems increase accuracy, they may reduce user comfort and increase system complexity.

In addition, recent work has focused on integrating HMR systems with Internet of Things (IoT) platforms to enable real-time monitoring and remote data analysis. Applications in healthcare, such as fall detection and rehabilitation monitoring, have shown promising results.

Despite these advancements, challenges remain, including sensitivity to sensor placement, variability among users, and computational constraints for real-time implementation. These limitations motivate the development of more robust, efficient, and user-friendly HMR systems using IMUs.

## X. PROPOSED METHODOLOGY

The proposed system aims to accurately recognize human activities using data collected from Inertial Measurement Units (IMUs) through an efficient and intelligent processing pipeline. The methodology integrates signal processing, feature engineering, and deep learning techniques to achieve high accuracy and real-time performance.

Initially, IMU sensors consisting of accelerometers and gyroscopes are placed on specific parts of the human body such as the wrist, waist, or ankle. These sensors continuously capture motion signals in three axes, including linear acceleration and angular velocity. The collected data is transmitted to a processing unit via wireless communication technologies such as Bluetooth or Wi-Fi.

In the preprocessing stage, raw sensor data is filtered using low-pass filters to remove noise and unwanted high-frequency components. The data is then normalized to ensure uniform scaling and segmented into overlapping time windows to effectively capture temporal motion characteristics.

Following preprocessing, a hybrid feature extraction approach is adopted. Statistical features such as mean, variance, and standard deviation are computed from each segment, while frequency-domain features are obtained using Fast Fourier Transform (FFT). In addition, the system leverages deep learning to automatically learn high-level features directly from the segmented data. For activity recognition, a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short- Term Memory (LSTM) networks is employed. The CNN component extracts spatial features from the input data, while the LSTM captures temporal dependencies and sequential patterns in human motion. This combination enhances the system’s ability to recognize both simple and complex activities. The model is trained using labeled datasets and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Hyperparameter tuning and optimization techniques are applied to improve model performance and reduce overfitting

Finally, the system is integrated with IoT for real-time monitoring and communication. Recognized activities are transmitted to a cloud platform, where they can be visualized and analyzed through a user interface or dashboardThis proposed methodology ensures improved accuracy, robustness, and scalability,making it suitable for applications in healthcare monitoring, fitness tracking, and smart wearable systems.

**Waste Segregation Approach**
The proposed system incorporates an intelligent waste segregation mechanism by combining Human Motion Recognition (HMR) using Inertial Measurement Units (IMUs) with sensor-based classification techniques. The goal is to automate and improve the accuracy of separating different types of waste such as biodegradable, non- biodegradable, and recyclable materials.

Initially, IMU sensors are used to recognize human actions involved in waste disposal, such as approaching the bin, hand movement, and object dropping. By analyzing motion patterns, the system detects when a disposal event occurs and triggers the segregation process.Once waste is detected, additional sensors are employed to identify the type of waste:

**Moisture sensors**
To detect wet (biodegradable) waste**Metal sensors** to identify metallic objects

**Infrared (IR) or optical sensors** to distinguish plastic and dry waste
The system processes the sensor inputs using a microcontroller or embedded system. Based on predefined thresholds and classification logic, the waste is categorized into different types.
An automated mechanism, such as a motorized flap or conveyor system, is then activated to direct the waste into the appropriate bin. The IMU-based motion recognition ensures that segregation is only triggered during actual disposal events, reducing false operations and saving energy.

Additionally, IoT integration enables real- time monitoring of waste levels and segregation status. Data is transmitted to a cloud platform, allowing authorities to track bin usage, optimize collection schedules, and ensure proper waste management.

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**Key Advantages**

improve accuracy of waste segregation Reduces human intervention and manual errors Enables smart and hygienic waste management. Supports real-time monitoring and control Can be integrated into smart city systems

**Power Supply and Energy Management**

Efficient power supply and energy management are critical for the reliable operation of Human Motion Recognition (HMR) systems using Inertial Measurement Units (IMUs), especially in wearable and portable applications. The system is designed to ensure continuous operation while minimizing energy consumption.

The primary power source for the system is typically a rechargeable battery, such as a lithium-ion or lithium-polymer battery, due to its compact size, high energy density, and suitability for wearable devices. In some cases, the system can also be powered through USB or external adapters during development and testing.

Voltage regulation is an essential component of the power system. Voltage regulators or DC-DC converters are used to provide stable voltage levels required by IMU sensors, microcontrollers, and communication modules. This ensures consistent performance and protects components from voltage fluctuations.

To improve energy efficiency, several power management techniques are implemented. The system uses low-power IMU sensors and microcontrollers that support sleep or idle modes. During periods of inactivity (e.g., no motion detected), the system enters a low- power state to conserve energy. The IMU can be configured to generate interrupts when motion is detected, which wakes up the system for processing.

Data transmission, especially via wireless communication (Bluetooth or Wi-Fi), is one of the most power-consuming operations. To address this, the system optimizes communication by transmitting data only when necessary (event-driven transmission) or at predefined intervals. Data compression techniques may also be applied to reduce transmission load.

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