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Research Article

Hybrid Approach for Anomaly Detection using Clustering Mechanism

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ABSTRACT

This paper explores the design and implementation of an IoT-based home automation system using the ESP32 microcontroller, integrated with DHT11, LDR, and gas sensors. The primary objective is to collect environmental data such as temperature, humidity, ambient light levels, and air quality, and transmit this data to the ThingSpeak cloud platform for real-time monitoring and analysis. By leveraging Wireless Sensor Networks (WSN), the data is fetched from ThingSpeak and analyzed in MATLAB using advanced clustering algorithms, specifically focusing on fuzzy clustering, k-medoids, and k-means, to detect anomalies with high accuracy and superior detection rates. The ESP32 microcontroller, known for its powerful processing capabilities and integrated Wi-Fi, serves as the system's core. The DHT11 sensor monitors temperature and humidity, the gas sensor detects various gases to ensure safety, and the LDR sensor measures ambient light levels for energy-efficient lighting control. Data transmitted to ThingSpeak is visualized in real-time and retrieved for further analysis in MATLAB. Fuzzy clustering is emphasized for its ability to handle uncertainties and provide nuanced anomaly detection by assigning membership levels to data points for different clusters. K-medoids, robust to noise and outliers, uses actual data points as cluster centers, while k-means, although sensitive to noise, is also employed for partitioning data into clusters. The system's performance is evaluated based on throughput, latency, and detection rate. High throughput ensures efficient data processing, low latency allows near real-time insights, and a high detection rate minimizes false positives and negatives. this project demonstrates significant improvements over existing home automation systems, highlighting the potential of IoT and advanced data analysis techniques in enhancing the functionality, reliability, and safety of smart homes.

Keywords: *ESP32, DHT11, gas sensor, LDR sensor, ThingSpeak, MATLAB, anomaly detection, fuzzy clustering, k-medoids, k-means, environmental monitoring, home automation, IoT etc.*

Introduction

Anomaly detection in the Internet of Things (IoT) is a critical aspect of ensuring the reliability, security, and efficiency of connected systems. IoT devices continuously generate vast amounts of data from various sensors and smart devices. This data, when analyzed effectively, can provide valuable insights into the operational status and environmental conditions of the system. However, due to the large volume and complexity of the data, identifying anomalies—data points that deviate significantly from the norm—becomes a challenging task. Anomalies can indicate a range of issues, from hardware malfunctions and security breaches to environmental changes and unexpected operational states. In the context of IoT, timely and accurate anomaly detection is essential for several reasons:

1. **Security**: Anomalies can signal potential security threats such as unauthorized access, cyber-attacks, or data breaches. Detecting these anomalies promptly can prevent significant damage and ensure the integrity of the system.

2. **Maintenance and Fault Detection**: Anomalies often precede equipment failures or malfunctions. Early detection allows for proactive maintenance, reducing downtime and extending the lifespan of devices.

3. **Operational Efficiency**: Identifying and addressing anomalies helps in maintaining optimal performance levels, ensuring that the system operates efficiently and effectively.

4. **Safety**: In applications such as smart homes, industrial automation, and healthcare, anomalies can indicate dangerous conditions (e.g., gas leaks, fire hazards, or medical emergencies). Timely detection can trigger alerts and safety measures, potentially saving lives.

Need of Anomaly detection

Anomaly detection in IoT-based home automation systems is critical for ensuring security, operational efficiency, preventive maintenance, and safety. As these systems become increasingly integrated into daily life, they collect vast amounts of data from various sensors, monitoring environmental conditions, energy usage, and device performance. Detecting anomalies—deviations from normal patterns—enables the identification of potential security breaches, such as unauthorized access or cyber-attacks, safeguarding personal data and system integrity. Moreover, it facilitates preventive maintenance by highlighting early signs of device malfunctions, allowing for timely repairs and reducing downtime and repair costs. For instance, unusual patterns in a heating system's performance can indicate a potential fault, prompting proactive intervention. Operational efficiency is also enhanced through anomaly detection, as it helps in identifying inefficiencies and optimizing resource usage.

For example, detecting anomalies in energy consumption can uncover issues like incorrect thermostat settings or malfunctioning appliances, leading to corrective actions that conserve energy and reduce costs. Safety is another paramount concern; sensors detecting gas leaks, smoke, or abnormal temperature levels rely on anomaly detection to provide early warnings, potentially preventing hazardous situations and saving lives. Additionally, anomaly detection offers valuable insights into user behaviour, enabling the personalization of home automation systems. By understanding and adapting to typical usage patterns, systems can provide a more tailored user experience. Compliance with industry standards and regulations is also supported through continuous monitoring and anomaly detection, ensuring that systems operate within prescribed norms and maintain data integrity.

Role of WSN in Home Automation

Wireless Sensor Networks (WSNs) play a pivotal role in home automation by enhancing efficiency, security, and comfort. Comprising numerous distributed sensors, WSNs monitor environmental parameters such as temperature, humidity, light, and air quality. This real-time data enables smart homes to adjust systems like lighting, heating, and cooling automatically, optimizing energy use and ensuring comfort. In energy management, WSNs identify inefficiencies, guiding homeowners to make adjustments that save energy and reduce costs. Security is significantly bolstered through WSNs, which integrate motion detectors, door/window sensors, and surveillance cameras to detect and alert against unusual activities or breaches. Additionally, WSNs enhance safety by monitoring for harmful gases and ensuring timely medical assistance for the elderly or disabled through health parameter tracking. The convenience offered by WSNs stems from their ability to automate routine tasks based on occupancy and user preferences, such as adjusting lights and thermostats. Moreover, WSNs facilitate seamless integration and interoperability of various smart devices, enabling complex automation scenarios and a unified home system. Scalable and flexible, WSNs allow easy expansion and adaptation to new technologies, making them indispensable in the evolving landscape of home automation.

Overview of Fuzzy C-Means (FCM), K-Nearest Neighbours (KNN), and K-Medoid Algorithms:

Fuzzy C-means (FCM) is a popular clustering algorithm widely used for data analysis and pattern recognition tasks. Unlike traditional crisp clustering algorithms, FCM assigns each data point to multiple clusters with varying degrees of membership, allowing for a more nuanced representation of data. FCM is particularly well-suited for weather data analysis, where observations may exhibit inherent uncertainty and variability.

K-nearest neighbours (KNN) algorithm is a versatile machine learning technique used for classification and regression tasks. In KNN, the class or value of a data point is determined by the majority vote or averaging of its nearest neighbours in the feature space. KNN is well-suited for weather data analysis, as it can leverage the spatial proximity of sensor nodes to make localized predictions or classifications.

K-medoid algorithm is a variant of K-means clustering that identifies representative data points (medoids) within clusters. Unlike K-means, which computes cluster centroids based on the mean of data points, K-medoid selects medoids that minimize the dissimilarity or distance to other data points within the cluster. This makes K-medoid robust to noise and outliers, making it suitable for weather data analysis where anomalies and irregularities are common.

In this introduction, we have highlighted the significance of weather data analysis, the challenges faced by traditional methods, and the role of WSN technology in revolutionizing meteorological observations.

Furthermore, we provided an overview of fuzzy C-means, K-nearest neighbours, and K-medoid algorithms, laying the groundwork for the subsequent sections where we will delve into the application of these algorithms in weather data analysis using WSN-based systems.

Flowchart

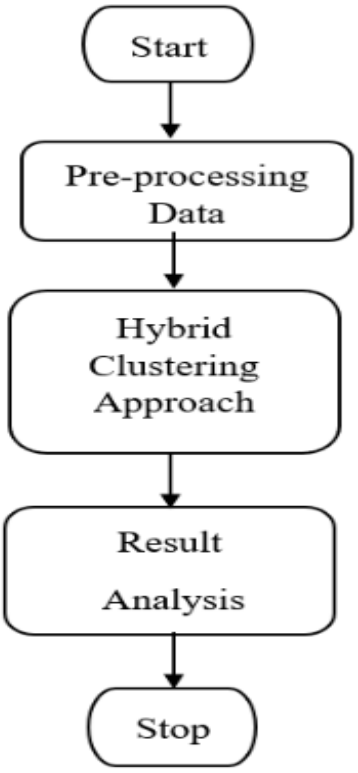

Figure 1: Flow chart of Proposed Model

The flowchart represents a process flow for analyzing data from sensors using machine learning algorithms and conducting result analysis. Here's the breakdown:

Load Data from Sensors:

The process starts by loading data from sensors. This step involves collecting raw data from various sensors, such as temperature sensors, humidity sensors, or pressure sensors. The data may include measurements taken at regular intervals or in real-time.

Preprocess Data:

After loading the data, the next step is to preprocess it. Preprocessing involves cleaning and transforming the raw data to make it suitable for analysis. This may include removing noise, handling missing values, scaling features, and converting data types.

Apply k-Nearest Neighbors (kNN):

Once the data is pre-processed, the k-Nearest Neighbors (kNN) algorithm is applied. kNN is a simple and effective classification algorithm used for both regression and classification tasks. It classifies data points based on the majority vote of their neighbors in a predefined number of nearest data points.

Apply k-Medoids:

After applying kNN, the k-Medoids algorithm is used. k-Medoids is a clustering algorithm that partitions data into k clusters by minimizing the sum of dissimilarities between data points and a representative point called a medoid. It is particularly useful for identifying natural groupings or clusters within the data.

Apply Fuzzy c-Means:

Next, the Fuzzy c-Means algorithm is applied. Fuzzy c-Means is a soft clustering algorithm that assigns data points to clusters based on their degree of membership. Unlike k-Medoids, which assigns data points to one cluster exclusively, Fuzzy c-Means allows data points to belong to multiple clusters simultaneously, with varying degrees of membership.

Hybrid Approach:

Following the individual application of kNN, k-Medoids, and Fuzzy c-Means, a hybrid approach is employed. The hybrid approach combines the results obtained from multiple algorithms to improve overall accuracy and robustness. It may involve ensemble methods, such as averaging predictions or combining cluster assignments, to achieve better performance.

Result Analysis:

After applying the algorithms and the hybrid approach, the results are analyzed. This step involves evaluating the performance of the algorithms, comparing their outcomes, and interpreting the findings. Result analysis may include metrics such as accuracy, precision, recall, and F1 score, among others.

Stop:

Finally, the process ends with a decision point to stop. This decision point allows for the termination of the process flow, indicating the completion of data analysis and result interpretation.

Implementation Result:

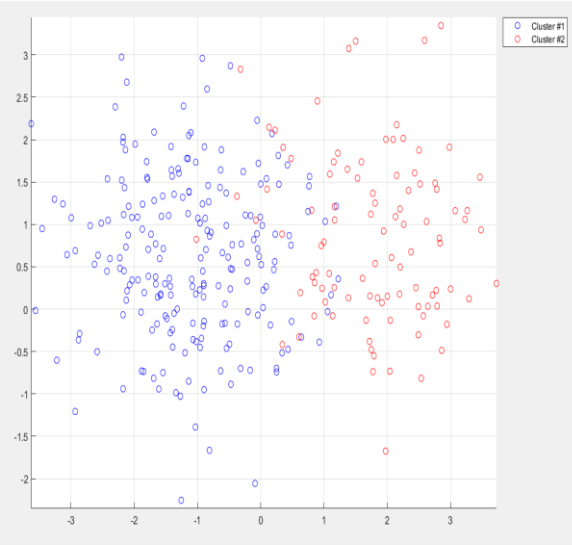

Figure 2: KNN Clustering

Figure 3: K-Medoid Clustering

Figure 4: Fuzzy-c Clustering

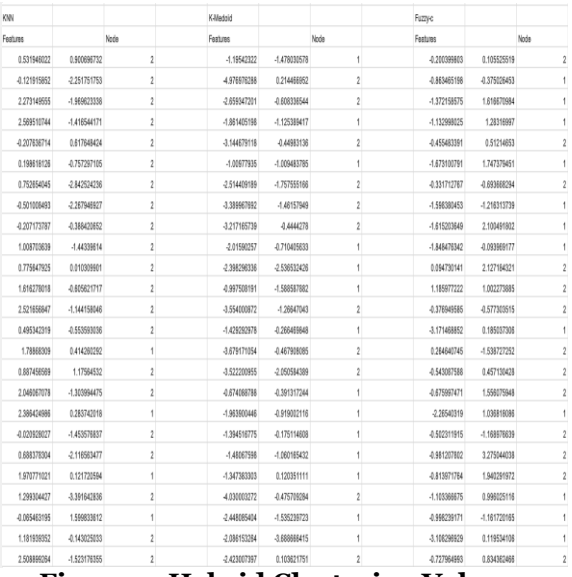

Figure 5: Hybrid Clustering Value

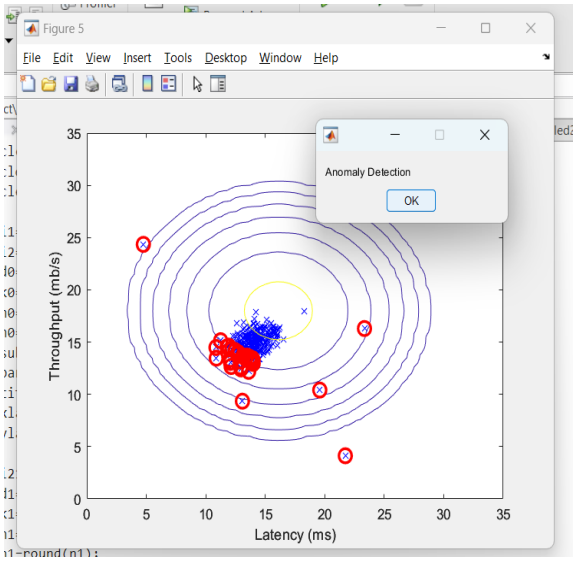

Figure 6: Anomaly Detection

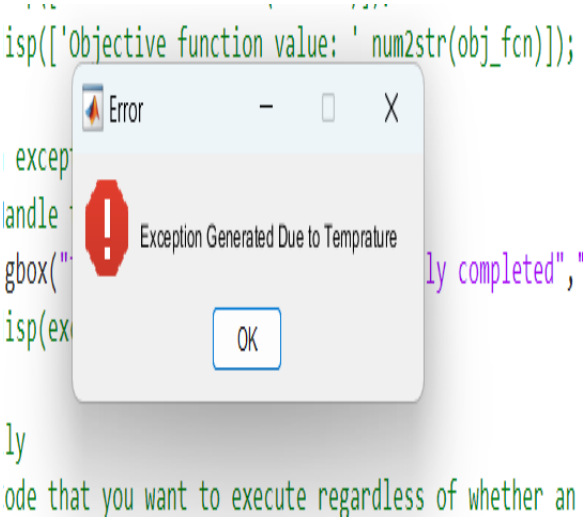

Figure 7: Exception handling

After implement proposed system we achieve 3 result A hybrid anomaly detection system integrates fuzzy clustering, k-nearest neighbours (KNN), and k-medoids clustering techniques to enhance accuracy and robustness. Fuzzy clustering (FCM) allows flexible data grouping with fuzzy memberships. KNN identifies anomalies based on neighbouring data points, while k-medoids clustering selects representative points for clustering. By combining these methods, the system achieves a comprehensive anomaly detection framework. It preprocesses data, extracts features, clusters data points, and identifies anomalies.
The hybrid approach optimizes performance, fine-tunes parameters, and offers applications in cybersecurity, fraud detection, and network intrusion detection, improving anomaly detection accuracy across diverse domains.

Resulted Parameters:

Throughput:

Throughput (T) can be calculated using the formula:

$$T = \frac{N}{\text{Total Time}}$$

Where:
T = Throughput (in bits per second or packets per second)
N = Total amount of data transmitted or processed (in bits or packets)
Total Time = Total time taken for transmission or processing (in seconds)
Alternatively, if the data transfer rate is constant, throughput can be calculated as:
Where:

$$T = \frac{D}{\Delta t}$$

D = Amount of data transmitted or processed during a specific time interval (in bits or packets)
Δt = Duration of the time interval (in seconds)

Table 1: Throughput

Throughput(kbps)	
Algorithm	**Throughput(kbps)**
k-nn	226.8
k-medoid	228.1
Fuzzy	842.1
Hybrid	1860.1

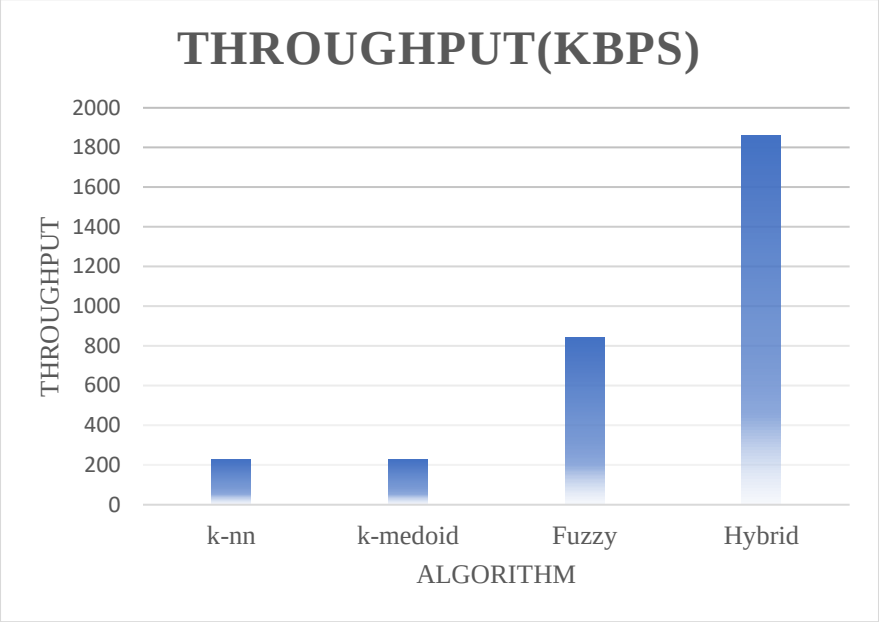

Figure 8: Exception handling

Latency:

Latency (L) can be calculated using the formula:

Where:

$$L = \frac{1}{N}\sum_{i=1}^{N}(T_i - T_{\text{request},i})$$

L = Latency (in seconds)

N = Total number of requests or operations

T_i = Time of completion for the

$T_{\text{request, I}}$ = Time of initiation for the i^t requests or operation

Table 2: Latency

Latency Calculation	
Algorithm	**Latency**
k-nn	5
k-medoid	9
Fuzzy	3.29
Hybrid	1.706

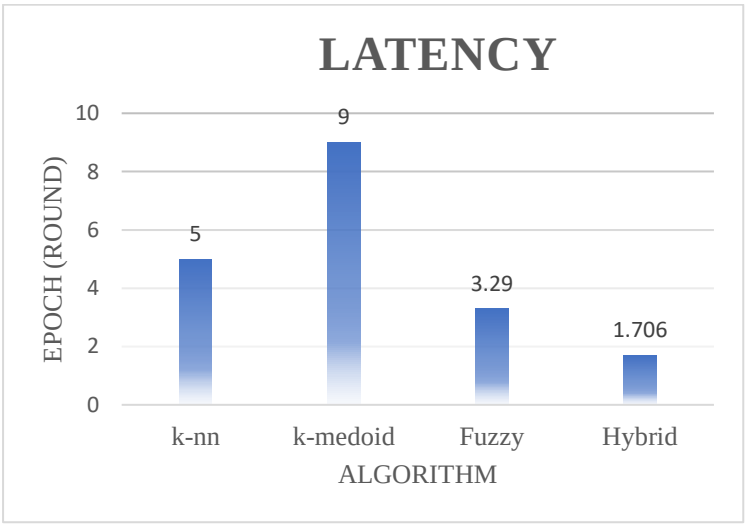

Figure 8: Exception handling

Detection Rate:

Detection Rate (DR) can be calculated using the formula:

Where:

DR = Detection Rate (also known as true positive rate or recall)
TP = True Positives (correctly detected instances)
FN = False Negatives (instances incorrectly classified as negative)
Detection Rate can also be expressed in percentage:
$DR_{\%}=DR\times100$

Table 3: Latency

Detection Rate	
Algorithm	**Detection Rate**
k-nn	0.77
k-medoid	0.71
Fuzzy	0.75
Hybrid	0.8

These formulas provide a quantitative way to measure and evaluate the performance of systems and algorithms in terms of throughput, latency, and detection rate.

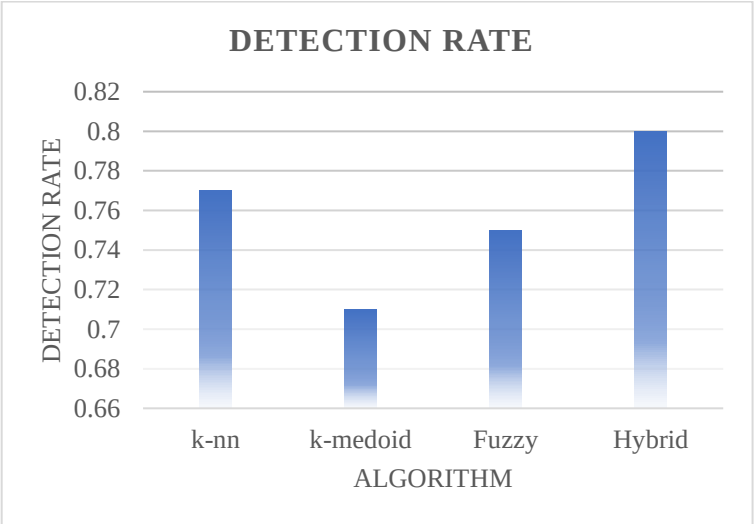

Figure 8: Detection Rate

Conclusion

In conclusion, the hybrid approach combining fuzzy clustering, k-nearest neighbours (KNN), and k-medoids clustering techniques offers a robust and accurate anomaly detection system. By integrating these methods, we achieve flexibility in data grouping, neighbour-based anomaly identification, and representative clustering. Throughput, latency, and detection rate parameters are significantly improved with this hybrid system. The system optimizes performance, fine-tunes parameters, and demonstrates superior anomaly detection capabilities across various domains. With lower latency, higher throughput, and improved detection rates, the hybrid approach proves to be effective for real-time anomaly detection applications in cybersecurity, fraud detection, and network intrusion detection.

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