

Detecting Context Inconsistencies in Context-aware IoT Applications

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Article Link: <https://www.brainetwork.org/index.php/jcai/article/view/169>

DOI: <https://doi.org/10.69591/jcai.3.1.5>



Volume 3, Issue 1, 2025

Funding

No

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Citation: Soomro, A. K., Malkani, Y. A., Dhomeja, L. D., & Samoon, S. (2025). Detecting context inconsistencies in context-aware IoT applications. *Journal of Computing and Artificial Intelligence*, 3(1).

Conflict of Interest: Authors declared no Conflict of Interest

Acknowledgment: No administrative and technical support was taken for this research

Article History

Submitted: Mar 10, 2025

Last Revised: May 27, 2025

Accepted: June 29, 2025



An official Publication of

Beyond Research Advancement & Innovation Network, Islamabad, Pakistan

Detecting Context Inconsistencies in Context-aware IoT Applications

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Abstract

The Internet of Things (IoT) is a rapidly growing technology that is transforming various domains such as smart homes, smart cities, healthcare, and transportation. IoT is the system of interconnected devices connecting to the internet to transfer and receive data with each other. IoT has developed in the number of context-aware applications where IoT applications automatically response to events triggered by contextual information, hence this feature can enhance user experience and facilitate the system with intelligent decision-making. IoT context aware applications are heavily rely on the contextual information to operate intelligently, therefore there is the growing demand for robust solutions to address the challenge of context inconsistencies. Inaccurate, incomplete or mismatched context readings from multiple sensors, is termed as context inconsistency. This context inconsistency in IoT applications can arise due to several factors, such as sensor noise, communication errors, and conflicting data from different sources. These inconsistencies can lead to inaccurate data processing, which can result in poor decision making and may cause damage in terms of time, labor, cost and even cause life threats. To address this critical issue, in this paper we propose an approach that detects context inconsistency in IoT. Further, the implementation of the proposed system is also presented in the paper.

Keywords: context awareness, context inconsistency, contextual information.

Introduction

In recent years Internet of Things (IoT) has developed enormously. Internet of Things (IoT), introduced by Kevin Ashton in 1999 refers to a system of interconnected devices connect to the internet to transfer and receive data with each other [1]. The core idea of IoT is that, the devices can automatically collect, process, and exchange data with one another without human intervention. Currently , IoT technology is widely applied in a variety of applications, such as smart homes, smart cities, industrial automation, healthcare, transportation, etc, however, IoT still faces several research challenges that need to be addressed. Several studies such as [2][3][4][5][6][7] exists that highlighted different research challenges (including device management, service management, interoperability, context-awareness etc.) in IoT that need to be addressed so the IoT systems work efficiently. Among these research challenges, context-awareness has received less attention from the research community.

In IoT, billions of devices are communicating over the Internet. These devices are used for sending information about themselves, their surroundings etc. This information is known as Context. IoT applications that utilize context are considered as context-aware IoT applications. With this context-awareness ability, IoT applications discover and adapt themselves based on the contexts. IoT has grown exponentially in context-aware applications to offer users with personalized services, improves their experiences, enables intelligent decision-making and provides real-time insights. However, the growing use of contextual information in IoT applications has created a need for effective solutions to address the challenge of context inconsistencies.

Context inconsistency can be defined as a situation in which two or more pieces of contextual information that describe the same real-world entity or phenomenon are mismatch or conflicting. For example, one sensor may detect that a room is occupied while another indicates that it is empty, or a one temperature sensor may report 20°C while a co-located sensor reports 38°C at the same time. Sensors noise, communication errors, and conflicting data from different sources are some of the common causes of context inconsistencies

These context inconsistencies cause threats to the normal behavior and reliability of context-aware IoT applications, which may cause complete application failures and may cause damage in terms of time, cost and life threats. Therefore, addressing context inconsistency detection and resolution is current need of the time to ensure the reliability and safety of context-aware IoT applications, mitigating the risk of application failures and other potential damages in terms of time, cost and lives. This paper addresses this issue of context inconsistencies in IoT environments and proposes a detection approach to effectively identify them. The proposed approach helps maintain consistency within context-aware IoT systems.

The remaining part of this paper is organized as follow: Section II summarizes the existing research work of context inconsistency detection and resolution for IoT. Section III describes proposed method of context inconsistency detection and resolution. Section IV gives implementation of the proposed system. Evaluation of the implemented system are presented in section V. Finally, conclusion of the paper is presented in section

Literature Review

IoT has become a rich area of research because of its vast and wide-ranging applications, it is still in evolving stage. Despite significant progress in different domains, various research challenges remain and must be addressed to fully realize its potential. There exist several surveys such as [2][3][4][5][6][7] that highlight research challenges that must be addressed for successful IoT deployment.

One major challenge is interoperability [2][3][4][5][6] is due to the immense

heterogeneity of IoT systems, meaning that different IoT systems must be able to work together seamlessly and can effectively communicate with each other.

Another key challenge is device management [3] , as the number of connected devices through the network continues to grow, there is the need to manage IoT devices. To address this challenge, various IoT device management platforms and protocols have been developed to enable efficient device control.

In addition, IoT systems often face major scalability challenges [4][5] due to the massive and rapidly increasing number of connected devices and the huge volumes of data they generate

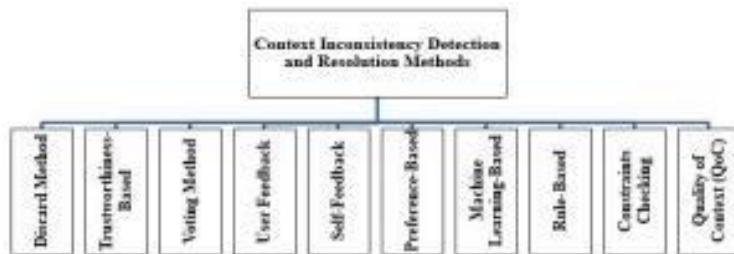
Security and privacy [2][3][4][5] represent significant concerns, as billions of IoT devices generate sensitive data increasing risk of security breach, unauthorized access and malicious attacks. Moreover, devices seamlessly connect and communicate with each other over the internet that also exposes the network to various security threats and attacks. Many researchers have been working on IoT security and privacy challenges to protect data and to establish secure communication between IoT devices, thereby ensuring confidentiality, integrity, and trustworthiness.

Finally, context-awareness [5][6][7] is an essential research area. It is an enabling technology for the Internet of Things (IoT), as it makes IoT systems smarter by enabling them to recognize and adapt their behavior dynamically in response to contextual information such as location, activity, or environmental conditions. However, the effectiveness of context-awareness depends on the accuracy and reliability of the contextual information being utilized. Inconsistencies in context data, arising from sensor errors, conflicting information, or incomplete data, can significantly reduce the performance of IoT applications. Therefore, to fully exploit the potential of IoT, it is essential not only to incorporate context-awareness for intelligent, flexible, and efficient operation, but also to address context inconsistency to ensure the correctness, reliability, and trustworthiness of context-aware decisions across diverse application environments.

Among the aforementioned research challenges in IoT, this research focuses on context inconsistency, which is key challenge within context-aware IoT environments.

In recent years, numerous strategies have been proposed by researchers to address the challenge of context inconsistency from different perspectives. These existing methods and strategies of the detection and resolution of context inconsistencies are well classified as shown in Fig.1 by [8].

Figure 1. Classification of Approaches for Detecting and Resolving Context Inconsistency [8]



Early approaches employed relatively simple techniques such as the discard method [9], [10], [11], the voting method [12], and the trustworthiness method [13]. Although straightforward, these methods demonstrated limited accuracy and were unable to satisfy the requirements of many practical applications. To enhance performance, subsequent studies introduced user feedback mechanisms for adaptive inconsistency elimination [14], [15], [16]. However, frequent solicitation of user input interrupts users and contradicts the fundamental principles of ubiquitous computing. To address the issue of excessive user input, self-feedback mechanisms were introduced to estimate the probability of correctness (PoC) of context [17]. However, designing reliable self-feedback mechanism is challenging in resource-restricted IoT environments. Some approaches of detecting and resolving context inconsistency based on user preferences [18]. This method relies heavily on user preferences which makes it more challenging to implement for wider range of applications.

Although these methods provide significant improvements, they often fail to guarantee the adaptability and stability required across diverse application scenarios. Consequently, recent research has increasingly focused on the quality of context (QoC) parameters for handing context inconsistency. QoC serves as a key metric for evaluating the quality of contextual information in context-aware systems. Manzoor et al. [19] addressed context inconsistency by incorporating different QoC attributes. Building upon this, another study [20] introduced a new (QoC) parameter relevance along with multiple QoC parameters to address issue of context inconsistency. Extending this line of work, another work [21] introduced a new overall quality indicator (OQoC) parameter leading to an inconsistency elimination algorithm integrates OQoC with D-S theory.

Beyond aforementioned techniques, several studies explored more advanced theoretical approaches. For example, theory of evidence or Dempster–Shafer (D-S) [20], [21], bayesian network [22], fuzzy logic [23] and the association rule mining [24], [25] has been extensively utilized to predict valid context values during

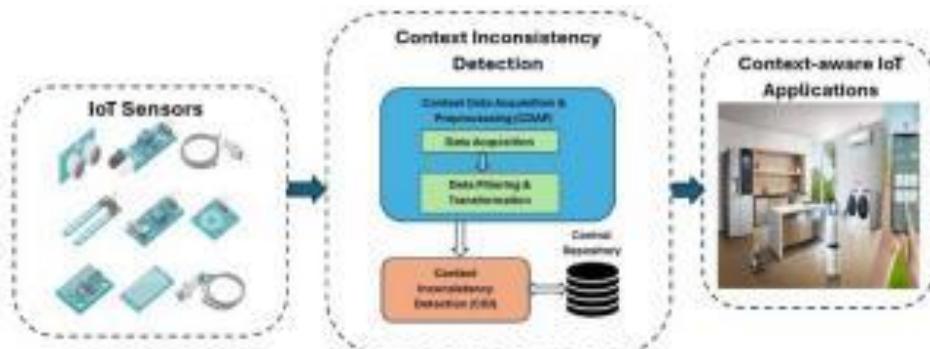
inconsistency elimination. In addition, refined algorithms have been proposed to address the conflict of evidence inherent in D-S theory [17], [18], while hybrid approaches integrating DS theory and fuzzy set theory have also been applied to the field of data fusion [19], [17].

In summary, current methods and integration of theories with the methods for context inconsistency detection and resolution in IoT systems have limited ability to achieve real-time adaptability and robustness and they lack to provide a generalized solution to cover wider range of IoT scenarios. Therefore, a generalized framework for context inconsistency detection and resolution for context-aware IoT systems needs to be developed which provides efficient solution and is suitable for wider range of IoT applications.

Proposed Methodology

Our proposed approach integrates context inconsistency detection and resolution to prevent applications from behaving anomalously. The system's architecture consists of five components as shown in Fig. 1. (1) Sensor component (2) Context Data Acquisition and Preprocessing (CDAP) (3) Context Inconsistency Detection (CID) (4) Repository component (5) Context-aware IoT Applications. The main components of this research are Context Inconsistency Detection. Each architectural component is discussed below.

Figure 2. Proposed System Architecture



Sensor component:

The sensor component consists of the third-party devices, that sense and collect data about surroundings either as analog or digital signals, which becomes the base for contextual data. There are number of sensors are available that can be used to sense and collect environmental data. In this research, we have used as temperature, humidity, light dependent resister (LDR) sensors. The selection of these sensors is based on their ease of use, availability and meeting design goal of this research.

CDAP:

Contextual data acquisition and preprocessing component is responsible for gathering raw data from diverse sources (i.e. sensors) and for preprocessing and transformation of raw data into context.

For example:

Raw Data:

LDR Sensor: 980

Motion Sensor: 1

Temperature Sensor: 38

Transformed/Processed Data:

Light: Very Dark

Movement: Detected

Weather: Very Hot

CID:

The CID component analyses processed context data to identify context inconsistencies. It evaluates data obtained from multiple sources and then verifies whether contextual information follows predefined rules. These inconsistencies occur when different sensors provide conflicting or mismatched contextual information about the same physical situation.

Repository component:

The centralized repository serves as the knowledge base of the system. It keeps track of the sensor's readings, the threshold values, and other past data that aids in recognizing and repairing inconsistent contexts.

Context-aware IoT Applications:

The component is the application layer where IoT-enabled devices and services work. The apps use the constant and reliable context provided by the system to deliver intelligent, adaptive, and personalized services to end users. An illustration of an IoT applications could be smart home systems, health monitoring platforms, and energy management etc.

Implementation

The proposed system has been partially implemented through Arduino and PHP. The system prototype collects sensor data in real time to detect inconsistencies in the collected information.

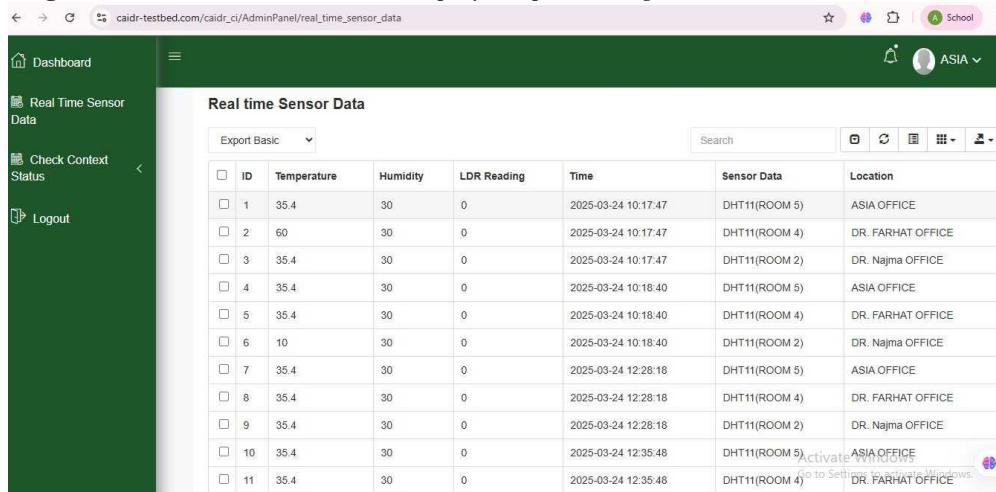
A web-based interface is developed which allows users to view IoT device data in real time and enables them to track context consistency.

The experimental setup uses an Arduino Wemos D1 board to connect with DHT11 sensors which measure temperature and humidity levels and an LDR sensor for light detection. The sensors data transmitted to the server through Wi-Fi before PHP scripts process and store it in a MySQL database. The web interface allows continuous monitoring, as shown in Fig. 1

Real-Time Sensor Data Acquisition

The system maintains a continuous flow of sensor data which includes temperature readings and humidity measurements and LDR values that get transmitted to the web application. The system shows environmental data through time-stamped tables which allow users to monitor real-time changes Figure. 3.

Figure 3. Real-Time Sensor Data Display Preprocessing



Real time Sensor Data							
Export Basic		Search					
	ID	Temperature	Humidity	LDR Reading	Time	Sensor Data	Location
<input type="checkbox"/>	1	35.4	30	0	2025-03-24 10:17:47	DHT11(ROOM 5)	ASIA OFFICE
<input type="checkbox"/>	2	60	30	0	2025-03-24 10:17:47	DHT11(ROOM 4)	DR. FARHAT OFFICE
<input type="checkbox"/>	3	35.4	30	0	2025-03-24 10:17:47	DHT11(ROOM 2)	DR. Najma OFFICE
<input type="checkbox"/>	4	35.4	30	0	2025-03-24 10:18:40	DHT11(ROOM 5)	ASIA OFFICE
<input type="checkbox"/>	5	35.4	30	0	2025-03-24 10:18:40	DHT11(ROOM 4)	DR. FARHAT OFFICE
<input type="checkbox"/>	6	10	30	0	2025-03-24 10:18:40	DHT11(ROOM 2)	DR. Najma OFFICE
<input type="checkbox"/>	7	35.4	30	0	2025-03-24 12:28:18	DHT11(ROOM 5)	ASIA OFFICE
<input type="checkbox"/>	8	35.4	30	0	2025-03-24 12:28:18	DHT11(ROOM 4)	DR. FARHAT OFFICE
<input type="checkbox"/>	9	35.4	30	0	2025-03-24 12:28:18	DHT11(ROOM 2)	DR. Najma OFFICE
<input type="checkbox"/>	10	35.4	30	0	2025-03-24 12:35:48	DHT11(ROOM 5)	ASIA OFFICE
<input type="checkbox"/>	11	35.4	30	0	2025-03-24 12:35:48	DHT11(ROOM 4)	DR. FARHAT OFFICE

The system applies context preprocessing to sensor readings before detecting inconsistencies by converting raw data into binary context values. The system achieves data standardization through this process which makes it easier to identify inconsistencies. The system defines specific threshold ranges for each sensor reading type through lower threshold (ThL) and upper threshold (ThH) values. The system transforms context values into binary data points through a process that sets values between ThL and ThH to "1" and all other values to "0".

After preprocessing, the context data sequence consists only of binary values (0 and 1). Figures 4,5 and 6 illustrate the binary conversion results for temperature, humidity and LDR contexts, respectively.

Figure 4. Temperature Context Status after Threshold-Based Conversion

Sensor	2025-03-24 10:17:47	2025-03-24 10:18:40	2025-03-24 12:28:18	2025-03-24 12:35:48	2025-03-25 12:41:27
DHT11(ROOM5)	1	1	1	1	1
DHT11(ROOM4)	0	1	1	1	1
DHT11(ROOM2)	1	0	1	1	1

Figure 5. Humidity Context Status after Threshold-Based Conversion

Sensor	2025-03-24 10:17:47	2025-03-24 10:18:40	2025-03-24 12:28:18	2025-03-24 12:35:48	2025-03-25 12:41:27
DHT11(ROOM5)	1	1	1	1	1
DHT11(ROOM4)	1	1	1	1	1
DHT11(ROOM2)	1	1	1	1	1
Status	Consistent	Consistent	Consistent	Consistent	Consistent

Figure 6. LDR Context Status after Threshold-Based Conversion

Sensor	2025-03-27 10:33:44
LDR(ROOM5)	1
LDR(ROOM4)	1
LDR(ROOM2)	1
Status	Consistent

Context Inconsistency Detection:

Once preprocessing is completed, the binary context data from multiple sensors is represented in the form of a matrix with size $M \times N$, where M represents rows of the matrix is the number of sensors and N represents columns correspond to context values collected at the same time across multiple sensors.

At each time step (column of the matrix), If the sum of binary values is equal to 0 or equal to the number of sensors (M), then all sensors report the same context then it is considered as context consistency Otherwise, if the sum lies between 0 and M ,

then at least one sensor reports a different value then it is considered as Context Inconsistency.

With this, context inconsistency is detected with a simple mathematical calculation. An example of the detection process is shown Figures 7,8 and 9. these figures illustrate the context inconsistency detection for temperature, humidity and LDR readings respectively.

Figure 7. CID (for Temperature)

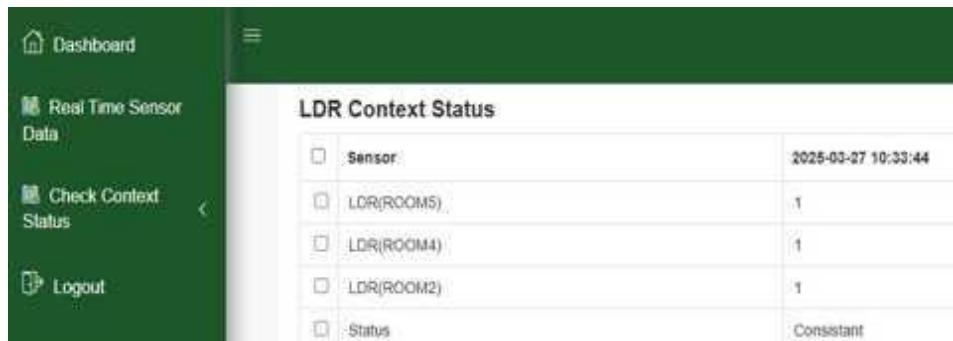


Sensor	2025-03-24 10:17:47	2025-03-24 10:18:40	2025-03-24 12:28:18	2025-03-24 12:35:48	2025-03-25 12:41:27
DHT11(ROOM5)	1	1	1	1	1
DHT11(ROOM4)	0	1	1	1	1
DHT11(ROOM2)	1	0	1	1	1
Status	In-Consistant	In-Consistant	Consistant	Consistant	Consistant

Figure 8. CID (For Humidity)



Sensor	2025-03-24 10:17:47	2025-03-24 10:18:40	2025-03-24 12:28:18	2025-03-24 12:35:48	2025-03-25 12:41:27
DHT11(ROOM5)	1	1	1	1	1
DHT11(ROOM4)	1	1	1	1	1
DHT11(ROOM2)	1	1	1	1	1
Status	Consistant	Consistant	Consistant	Consistant	Consistant

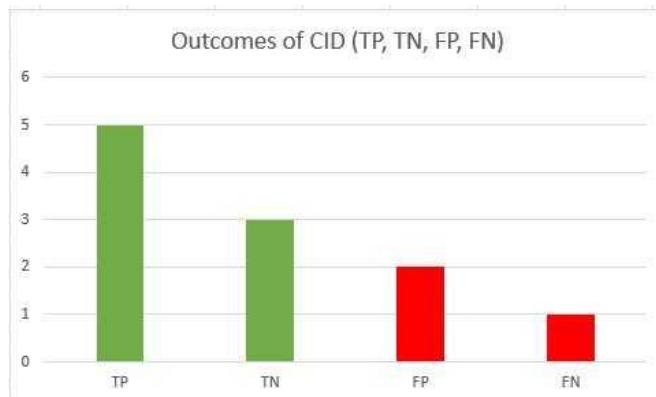
Figure 9. CID (For LDR)


LDR Context Status		
<input type="checkbox"/> Sensor	2025-03-27 10:33:44	
<input type="checkbox"/> LDR(ROOMS)	1	
<input type="checkbox"/> LDR(ROOM4)	1	
<input type="checkbox"/> LDR(ROOM2)	1	
<input type="checkbox"/> Status	Consistent	

Evaluation

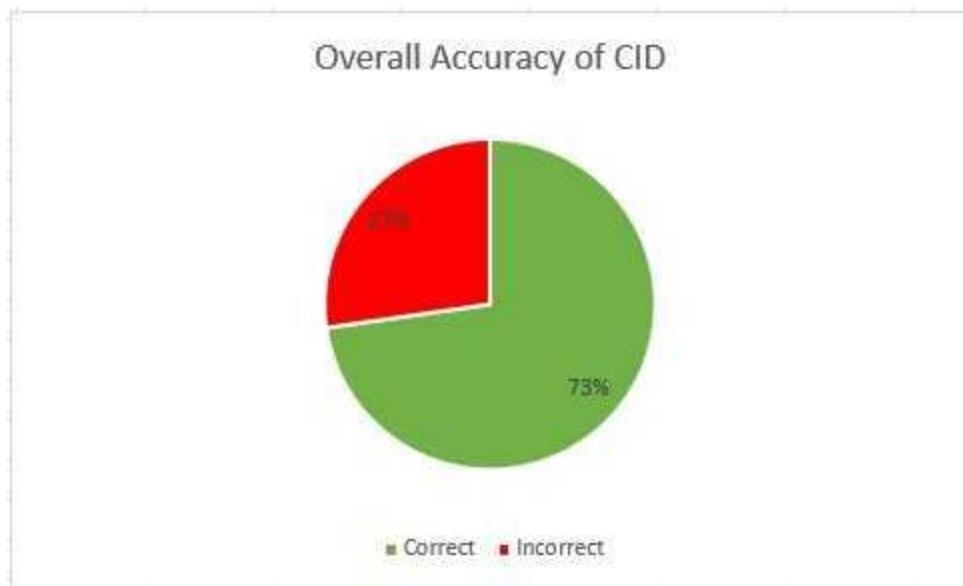
The performance of the system was evaluated using a confusion matrix. The confusion matrix provides classification results by comparing the actual context state with the predicted output generated by CID. Its outcome are True Positive (TP) which represents the number of instances where an inconsistency was correctly detected, True Negative (TN) denotes consistent contexts correctly identified, False Positive (FP) refers to cases where a consistent context was misclassified as inconsistent, and False Negative (FN) represents inconsistent contexts misclassified as consistent. The distribution of True Positives (TP) and True Negatives (TN) and False Positives (FP) and False Negatives (FN) shown in Figure 10. The system demonstrates high reliability in detecting consistent and inconsistent contexts because TP and TN values dominate the results.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Figure 10. CID (for Temperature)

The system accuracy calculated from the confusion matrix. The Context Inconsistency Detection (CID) approach received evaluation through a comparison between its prediction outcomes and the actual results. The system reached a total accuracy rate of 73% according to Figure 11. The pie chart demonstrates that the system correctly identified most contexts but produced incorrect results for 27% of cases.

Figure 11. Accuracy of CID



Conclusion

This research proposed a solution to handle context inconsistency problems that occur in context-aware IoT systems. The system provides a generalized method to detect context inconsistencies which works across multiple context-aware IoT application domains. The paper provides details on the implementation of context inconsistency detection (CID) mechanism. Furthermore, it evaluates the system by examining its performance by analysing its detection accuracy across different sensors. In future we will integrate the context inconsistency resolution approach into our existing architecture to eliminate context inconsistency once it is detected. This integration will allow the system not only to detect the context inconsistency but also resolve it automatically, allowing dynamic context-aware IoT environment to maintain consistent contextual information.

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