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Smart Devices, Smarter Data: Enhancing Quality in the Age of Ubiquitous Computing

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Abstract: Advanced advancements in computing technologies have seen smart technologies get integrated into society to the extent of forming nearly every component of societal life. These include wearable, home automation systems, Industrial IoT machines, and all the other IoT devices in the market that produce large data. This paper aims to explore the changing trends in leveraging ubiquitous computing to improve the quality and effectiveness of data. When it comes to numbers, managing a huge amount of connected devices and determining the accuracy and relevance of data at the proper time becomes difficult. To this end, in this paper, we define and discuss data intelligence within the context of UC, especially by reviewing mechanisms such as edge computing, Analytics, and Context Awareness. Besides, the paper explores factors such as architectural aspects, privacy concerns, standards requirements, and a discussion on the impact of interconnectivity on enhancing data environments. Based on the literature review study, methodological framework and experimentation, this paper presents an integrated approach to improve the data quality in the smart device context. Hence, it is possible to conclude that everyone could benefit from making the systems adaptive, decentralized and secure to enhance the outcomes of data processing in ubiquitous environments to support smarter decision-making across various fields.

Keywords: Ubiquitous computing, data quality, smart devices, edge computing, privacy.

1. Introduction

1.1 Importance of Enhancing Quality in the Age of Ubiquitous Computing

The constant and increased use of surrounding technologies has revolutionised life, introducing automation and personalisation features. However, the quality of the produced data is critical to these technologies' success; as data quality degrades, the efficiency of smart systems also declines. [1-4] Therefore, data quality improvement has been deemed necessary in the age of ubiquitous computing environments. Now let it be discuss five demands that specify the necessity of the increase in the quality of data nowadays.

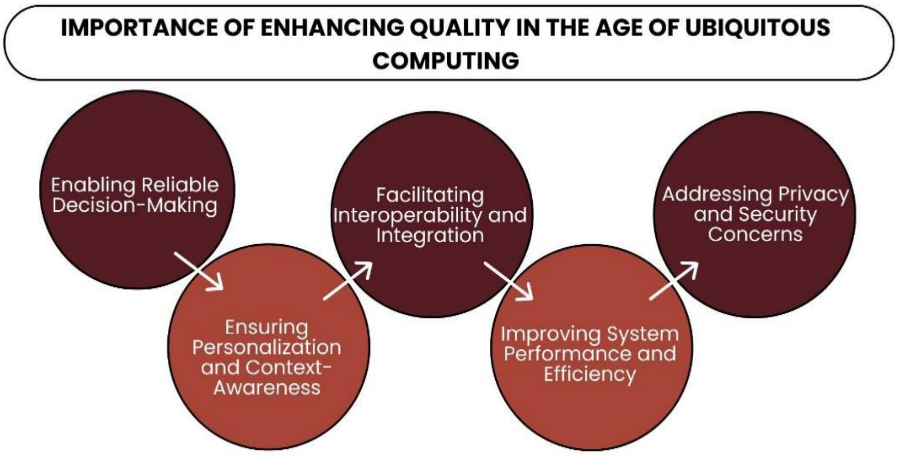

Figure 1: Importance of Enhancing Quality in the Age of Ubiquitous Computing

- **Enabling Reliable Decision-Making:** Smart environments are thus characterised by using data-driven decision-making as the main working model of the entire system. This is true whether it is an automobile on the roads or the health of a patient being recorded; the quality of data affects the system's overall capabilities. Data quality affects the quality of judgment, the decision-making process, and the functionality of smart systems and may bring fatal consequences in some cases. From what has been explained above, it is evident that better quality data can be more useful, this way making systems more reliable in delivering accurate, comprehensive, and timely decisions.
- **Ensuring Personalization and Context-Awareness:** Ubiquitous computing's primary characteristic is to provide customized services based on user needs that have emerged in recent years. There is no doubt that the concept of smart homes, smart wearables and other IoT devices gather huge amount of personal information for better service offerings, be it keeping tabs on the client's movement patterns to recommend a particular type of diet to even controlling the temperature of the home based on the activities of the residents. However, for these systems to be personalized, the data collected must be accurate and inclusive of all information related to the clients. Sophisticated

people are able to have better accuracy predictions and appropriate responses from the more comprehensive data-rich user experience.

- **Facilitating Interoperability and Integration:** This is due to the future smart environment, which comprises various devices from different manufacturers, and the performance of these devices must be integrated. First, it is necessary to state that the data in question must be compatible and homogeneous across the devices. Improving the data quality can help to perform data integration of data from several sources and make the IoT ecosystems heterogeneous systems operate properly. For instance, information must be formatted and delivered cohesively and effectively from light, security, heating, ventilation and air conditioning devices cohesively and effectively to form smart homes.
- **Improving System Performance and Efficiency:** For smart systems to perform optimally and avoid wastage of resources, the systems need to use constant inputs and outputs. For example, a smart thermostat changes temperature depending on the data about the activity of the owner of the house, and a smart grid regulates the electricity consumption depending on the demand. Compiling and using inexact or partial information may lead to poor organizational results, resource squandering, and increased operating costs. Therefore, smart systems working with higher-quality data can make better decisions, meaning better use of energy, use of resources, enhanced performance of the system in question, etc.
- **Addressing Privacy and Security Concerns:** Data quality is also heavily dependent on the issue of privacy and security. When personal devices connected to the internet are generating large amounts of data, including the data health of an individual, behavior patterns, and the position of an individual, the data mustn't be altered or accessed by an unauthorized person. Adherence to good quality data management principles such as data encryption and data security enhances user privacy while at the same time enhancing the validity of the processed data. Despite the growing number of breaches and instances of privacy invasions, precision in data to be fed to the smart systems is critical to the confidence in the systems amongst the users. The contextual quality of data in today's ubiquitous setting does not only center on refining clerical outcomes but on altering the way society and its members trust these systems and their capacity to respect privacy and even augment human endeavor. At the same time, we shall have to continue working towards elaborating the methodical and technical approaches for using IoT and other intellectual environments, as well as making sure that the results of their operation are as beneficial for society as possible and are devoid of negative consequences for people's lives.

1.2 Challenges in Data Quality

With regard to the values of information in the environment of the UBI, data become produced in a constant stream by the network of sensors and smart devices, billed by the peculiarities of a specific connection and individual qualities. This may cause many complications, which lean towards the data quality challenges. Redundancy, for instance, exists in the form of overlapping where several sensors are used to gather the same or similar information, creating a problem of duplicate data that congests the processing systems and helps degrade the effectiveness of analytics. [5,6] Another type of problem is for data collected from different devices to be formatted differently or to have different measurement units, making it hard to combine and analyze. Inaccuracy is an unwelcome occurrence when, instead of providing a true picture of reality, the data it feeds are erroneous due to sensor calibration, environment or even device failure. Last but not least, noise is the unwanted variation in data that is not due to the existence of any signal or can be said to be a disturbance or fluctuation in data which is not, in any manner, related to input or output variable or can be due to the external interference or some losses in the transmission line or due to the error occurred in the sensors.

This noise could interfere with the collected data, so any analysis picture would be distorted and not reflect what is real. Thus, based on these few examples, it is clear that data quality can be a significant problem, especially in smart environments where much of the decision-making is based on real-time data. People make mistakes, so wrong analysis and decisions can lead to poor system design, product or product/process design, system insecurity and unsatisfied users. As such, in health monitoring systems, it is catastrophic if the data received from the mobile device contains wrong information or is inconsistent with the information already available. This means there is a rise in the need to proactively address data quality challenges at the source, such as smart devices. Some of the issues encountered in later stages of data analysis can be prevented at the device or edge layer through outlier detection, normalization and data imputation. So, the guard against the above disadvantages, it is vital to ensure that data quality is optimally achieved during this stage to enhance the reliability of smart systems for real-life operations.

2. Literature Survey

2.1 Ubiquitous Computing and Smart Devices

Ubiquitous computing, now commonly known as pervasive computing, was first announced by Mark Weiser in early 1991. This concept has become a reality with the help of IoT, which refers to various connected smart devices that gather, process, and act upon necessary data with insignificant interference from the human side. [7-10] These include smart wristbands that monitor one's health and smart home appliances that are gradually adding to our pervasive computing environment. Their integration is essential in building smart healthcare, transport, and city systems and, therefore, requires accurate and high-quality data to feed the decision-making processes in the systems.

2.2 Data Quality Dimensions

It is thus imperative to evaluate the quality of data on various aspects of the functioning of smart systems. Accuracy involves how well the collected data measures up to the actual values of what it measures, especially a factor of great importance when measuring health statuses among other domains. Completeness is important since it guarantees that any important data necessary to analyse context or make decisions is not left out. In a scenario, timeliness indicates how recent the data is, which a system is of immense importance for time-sensitive applications such as self-driven cars or disaster management. Consistency is concerned with data organization since the same information should be placed similarly across different systems; consistent interpretation within each system minimizes confusion in smart environments.

2.3 Technologies Influencing Data Quality

In general, it can be stated that the following emerging technologies have a positive impact on the quality of the data collected in smart environments: Edge computing is the location where computations are done nearer to where the data is being generated to help deal with time, latency and other problems related with data transmission in a network. This enables the provision of up-to-the-minute information, which, in a way, promotes real-time decision-making and is efficient in providing timely information. Automation can be used to find outliers missing values, generate the predicted value and make the data more accurate and complete. This is true because blockchain data management applications offer decentralized, secure, and immutable records.

2.4 Challenges Identified

However, the following challenges affect the enhancement of high-quality data in a smart environment. Device heterogeneity is still crucial in smart systems because these systems can integrate various gadgets from different producers with different protocols, skills, and standards. This inconsistency poses a problem in the integration and management of data in the conducting of various activities. The social and political issue that can be identified is privacy since personal data is intensively collected, processed and disseminated, and questions arise regarding consent, protection, and appropriate use. Finally, promoting data governance seems crucial but under-discussed within these ecosystems. It covers guidelines for ethical, secure, and sound data management, but unfixed and non-existent governance has weaknesses that can affect the credibility and usefulness of smart systems.

3. Methodology

3.1 Research Design

This study adopts a mixed-method research approach to assess data quality in a smart environment by building models and experimentations. The reason for using such an approach is that this approach facilitates a connection between theory and practice. A hypothesis is conceptualising an overall view regarding the data quality dimension, including accuracy, completeness, timeliness, and consistency, and investigating their association with several enablers, such as edge computing, automation, and blockchain. [11-14] This model enables the specification of what variables, connections, and conjectures may be used for knowledge about data circulation, handling, and trustworthiness in ubiquitous computing environments. In order to ensure the practicality and robustness of these theoretical frameworks, the proposed framework is invoked in real-world conditions on a smart home testbed. This environment consists of a combination of IoT devices kept in a relationship that is connected to environmental sensors, home appliances, health-related displays, and security gadgets. Information is captured

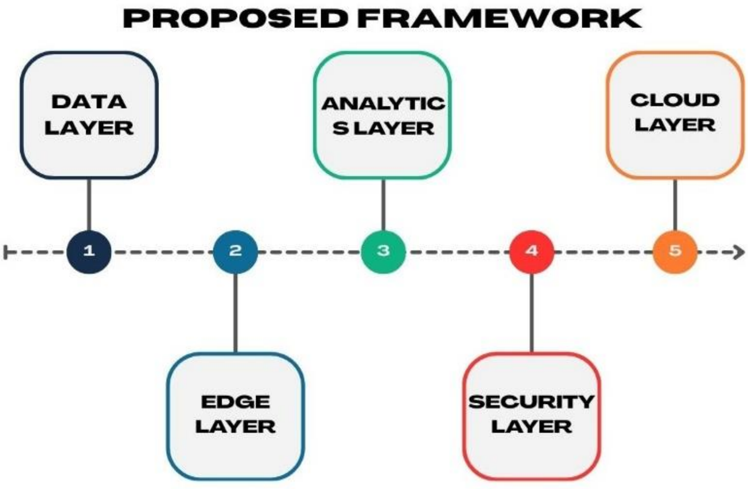

Figure 2: Proposed Framework

online at different parameters resulting from the actual functioning of the system, so there is a possibility to evaluate the influence of factors, such as device heterogeneity and different types of latency, on the quality of data generated and disseminated as well as types of processing data. The testbed is valuable not only to check on the model and its properties but also to reveal certain difficulties and constraints that otherwise can occur only in real life. Furthermore, both numerical and non-numerical information is collected for the assessment purpose. The Quantitative measures gauge the degree of accuracy, time and completeness of data under different arrangements, while qualitative metrics indicate user experience, system performance, and relevance of data. This research design that combines theoretical modeling and experimentation approaches guarantees to give the proposed and tested understanding of DQM in SE environments that is faithful and pragmatic and is likely to foster the implementation of robust and trustworthy smart systems.

3.2 Proposed Framework

- **Data Layer:** In the middle of the architecture design, the Data Layer comprises various data creation platforms, including sensors, cameras, wearables, etc. These components are meant to acquire real-time and raw data from the environment and users. This may involve temperature sensors, motion detectors, heart rate sensors or surveillance cameras in the smart home environment. The first and most essential characteristic is that the input for further analyses comes from various types of devices and includes substantially different data types. In this layer, its reliability and accuracy are most critical because any mistake made here will be reflected in the remainder of the system.
- **Edge Layer:** Explicit in the case of transactional data, it can be defined as the first layer of the data structure for further processing, which is closest to the data source. It mainly involves using micro controllers and fog nodes in that this layer carries out mainly the data filtering, normalization and pre-processing. Due to the processing of computations on the Edge Layer, latency and traffic load can be lowered to make faster responses for time-bound operations. It also ensures the timely and accurate entering of data since it reduces the occurrence of input-error-associated transmission. It is highly important in real-time conditions where some decisions should be made within the shortest possible time and may include sounding alarms or changing the environment.
- **Analytics Layer:** As for the Analytics Layer, it can be stated that they would involve further analysis processing using computing techniques. Automation is done here on the machine learning models to forecast future events and on the anomaly detection algorithms. This layer improves the smart environment's intelligence by bringing meaning to the raw and preprocessed data. For instance, it can estimate energy consumption habits, identify health concerns, or recommend automatic configuration with learned user patterns.
- **Security Layer:** Security is built into the system through the Security Layer, which uses such features as the blockchain and the encryption system. Blockchain is synonymous with non-alterability, accountability for the correct correlation, and immutability. It is used to avoid leakage of information when it is in movement and when it is being stored, whether it is health information or video stream. This layer concerns issues of privacy, trust, and ownership, which are crucial in smart environments to accept the schemes by the users and meet the demands of the regulations.
- **Cloud Layer:** The Cloud Layer is designed to be the storage and high-computational space of the system for the long term. It offers proven experience in data archival, model probationary and experiences in developing and implementing large-scale analytics. It also provides control and easy monitoring over the algorithm to fine-tune it or for further experience and valuable suggestions later with the result analysis of the cloud. This layer supports the edge and the analytic layer by offering the lion's share of resources and storing backup data for interval and historical intelligence.

3.3 Data Quality Enhancement Algorithms

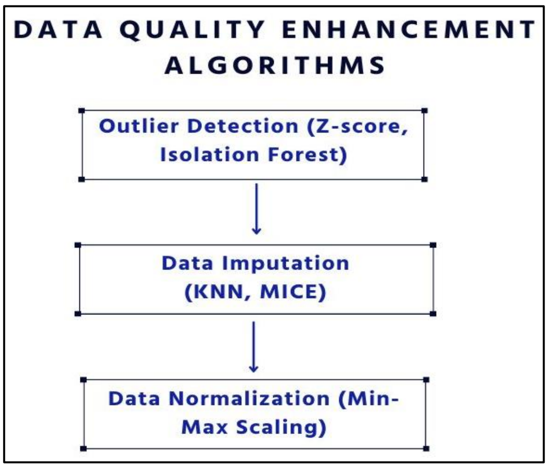

Figure 3: Data Quality Enhancement Algorithms

- **Outlier Detection (Z-score, Isolation Forest):** It is crucial in determining what can be referred to as an abnormality or an outlier that can lead to wrong decision-making in case it forms part and parcel of analysis in smart environments. Z-score is an efficient technique for identifying outliers in normal distribution for quantitative data.

[15-18] Nonetheless, Isolation Forest is another classification technique that works on isolated principles to isolate the instances or values randomly, so it is apt to work with different types of data high dimensional and non-linear data. Combining these approaches plays an important role in filtering out any potential errors that normally originate from errors in the functionality of the sensors or any other unpredicted events that may persist within the environment.

- **Data Imputation (KNN, MICE):** Data imputation deals with incomplete or missing values in a dataset, and this is quite rampant in smart environments due to power outages, lack of connectivity sometimes, or some device failure. The procedure of imputing missing data is done in K-Nearest Neighbors (KNN) imputation by calculating the average of the missing values from the nearest similar instances based on the feature space. Multiple Imputation by Chained Equations (MICE) is an advanced form of imputation as MI creates multiple imputations for each feature with missing values by modeling it depending on the other features iteratively. These methods enhance complete data, resulting in more accurate analytical models and reducing the chances of biased findings.
- **Data Normalization (Min-Max Scaling):** It is specifically important for algorithms highly sensitive to variations in magnitudes of the potential values or the numbers in the dataset since normalization brings data from different sources to a unified level. Min-Max Scaling is suitable for transforming data values into the range [0, 1] without enlarging or shrinking distinctions of the range of values. It is very useful, for instance, when integrating signals from different sensors with dissimilar units or measuring scales. Normalisation makes the output more interpretable and usable and brings all the dataset inputs to a comparable level to increase the efficiency in creating machine learning models.

3.4 Evaluation Metrics

As for the evaluation of the proposed framework and the applied data quality enhancement algorithms, the system's analytical performance and response time are measured. Precision and Recall are two of the most popular measures that are usually used in classification and for diagnostics of anomalies. Accuracy measures the extent to which the system can give correct positive results among all that it identified as positive, meaning that it will not give out wrong positive results. On the other hand, Recall evaluates the ratio of the actual positives to the total number of positives. Moreover, it provides a clue about the framework's capacity to identify all the positive cases, as in the cases of distinct data stream anomalies or outliers. Altogether, these measures give a fair picture of detection capabilities and are essential to assess such elements as anomaly detection based on Automation in the analytics layer. Besides the classification measures presented above we have also developed the Data Quality Index (DQI) that measures the general fitness of the data based on accuracy, completeness, timeliness, and consistency.

The DQI compiles such factors into a single indicator that allows for a clear data quality assessment across the system. In particular, using Curvature Analysis allows us to directly compare the impact of various preprocessing algorithms, methods of imputing missing values, and specifics of working in different devices. Hence, by measuring DQI from time to time it will help to determine the kind of improvement made in the quality of the data as well as whether the system is having a bottleneck or had a failure. As for the last one, Response Time is employed to measure the system's actual performance in real-time. It quantifies the time from data creation to the system's response, which is very important for real-time applications in smart environments such as health notifications, security breaches or automation control. High numbers are associated with poor data response time, flow, and processing, especially in the edges and layers of analytics. Using all these measures, we get a rather comprehensive approach to the subsequent assessment, which not only considers the accuracy of the findings but also the quality of the input data and the timeliness of the system's performance.

4. Result and discussion

4.1 Testbed Setup

The experiment for this study was conducted in a smart home testbed that was made to mimic a real home with several inter-connected IoT devices. It is equipped with ten devices or gadgets selected to cover the most relevant aspects of a smart home system. The system was projected onto these devices: smart lights for changing the light environment, smart thermostats for managing temperature, motion and temperature sensors for monitoring changes in the home environment, smart speaker for voice interaction and communication with the user, and three wearable health unidentified for tracking user activity, watch, heart rate monitor and sleep tracker. All the devices were connected through a local network and sent the data to the central hub for further handling and analysis. For this, the arrangement was made in a monitored typical residential environment to mimic the real-life use of the smart devices over some time as closely as possible.

The data collection was carried out over 7 days to understand its behavior under normal conditions and during some minor disturbances, e.g., loss of connectivity or failure of a particular device. There was about 20GB of multimodal data collected from 28 participants aged 19 to 69 with 13 males and 15 females during the same period from various parameters such as internal and external environments like temperature, light intensity and humidity, activity of the user such as motion and voice commands, and logs from the device as on/off state, timings among others. Therefore, the availability yielded a high-quality raw data set that allowed for data quality analysis and our proposed ordinance data quality enhancement technique. The testbed offered a realistic smart home framework for testing our system's performance under different conditions. It served as a good basis to study the effect of using our algorithms in enhancing data accuracy, completeness, and timeliness.

4.2 Data Quality Improvements

Table 1: Data Quality Improvements

Metric	Improvement
Accuracy (%)	14.3%
Timeliness (ms)	75%
Completeness (%)	12.7%

- **Accuracy 14.3% Improvement:** There was an enhancement of 14.3 %; the accuracy improved from 84.3% to 96.7% upon the use of the proposed framework. The main reason for the accuracy improvement was the application of junior advanced outliers' detection methods, such as Z-score and Isolation Forest algorithms, which helped filter out the wrong data resulting from sensors' failures or errors in the environment. Eliminating the possibility of including extreme values in the data reduced the risk in data analysis. It fed the data into analytics models as accurately as possible, enriching the system's outcomes.
- **Timeliness (ms) 75% Improvement:** Another assessed aspect was the timeliness, which stands for the system's reaction time. It was improved by 75 %, corresponding to 1200 ms and 300 ms. On this account, much of this improvement was due to the adoption of edge computing within the system. It was an added advantage since most of the processing was done at the edge layer, reducing the time required to access the cloud servers hence reducing delays due to the network. Real-time decision-making applications, which include smart lighting or environmental control, greatly benefited from this reduction to have better reaction time to the sensors' inputs, Client satisfaction, and system efficiency.

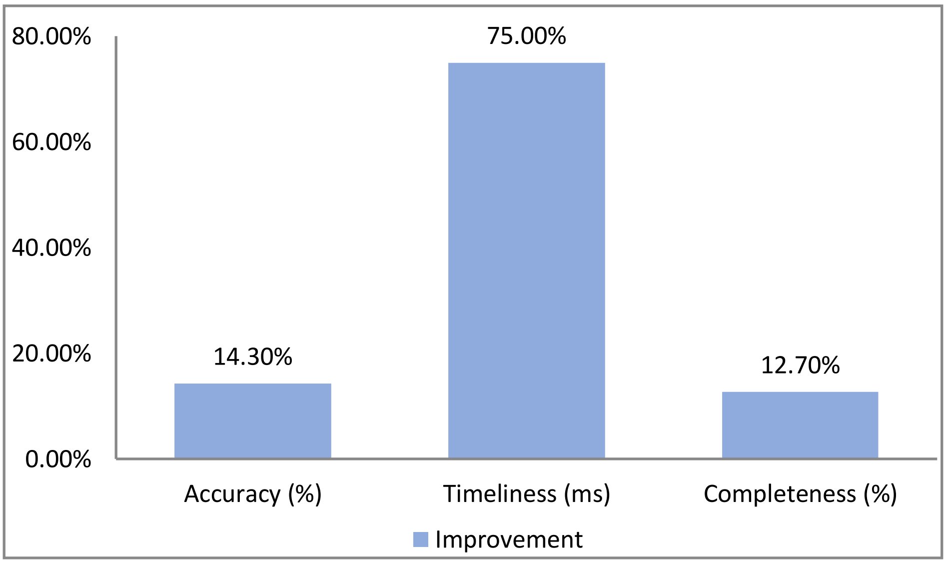

Figure 4: Graph representing Data Quality Improvements

- **Completeness (%) 12.7% Improvement:** This means that accomplishing the totality of data was enhanced by 12.7%, which was recorded as 87.5 and 98.2, respectively. This enhancement was justified using the Data imputation techniques for missing values by using KNN (K-Nearest Neighbors) & MICE (Multiple Imputation by Chained Equations). These algorithms provided the estimated values when some were missing or left blank because they depended on the relationship between other variables in that dataset. Therefore, the process was completed with higher accuracy, and this data remained stable and solid to be used in the next stages such as predictive analysis and anomaly detection.

4.3 Discussion

The results of this experiment support the effectiveness of the proposed data quality enhancement framework for a smart home environment to a large extent. Perhaps this investigation's first set of findings is the strong correlation between edge analytics and system performance. Through data processing, edge nodes, which are near the data source, minimise the usual latency expected when data is transmitted to the cloud data centers for calculations to be made. This reduction in latency ensured that responsiveness was nearly real-time; this is important in applications such as smart lighting or temperature changes. Thus, devices in a smart home can immediately become responsive and sensitive to changes in the environment and user interactions that, in turn, would improve the usability aspect of the smart home system and its general performance. The missing data were dealt with using two imputation techniques: imputation using KNN and imputation using MICE. There was a boost in data completeness and quantity as a result. These algorithms proved very useful in handling cases where there are data holes, usually caused by the sack of sensor data or interruption of the data transmission network. According to estimates made through the existing patterns or trends in the data, the framework could ensure that the dataset always remained complete and filled with valuable data for analysis and planning.

Last of all, the implemented Security Layer based on the principles of blockchain and end-to-end encryption guarantees data confidentiality and authenticity. The blockchain ensured that the data was secure and could not be changed. In contrast, the encrypted feature ensured that the sensitive information was not exposed or easily accessed by those who had not met the required legal and ethical considerations. From the top to the bottom, no breaches or unauthorized access were recorded during the experiment to show the level of security in the system. These are some of the reasons why this multiple-approach to data quality enhanced not only the detailed characteristics such as accuracy, time, and completeness of the data but also the reliability of smart homes, using this application to have confidence in its applicability.

5. Conclusion

This paper focuses on the importance of data quality in today's world of increasing use of smarter devices and sensors and generating huge amounts of data in various contexts. As these systems advance into our smart home, wearable health, autonomous vehicles, and smart and connected industries, the data, its accuracy, timeliness, and its being complete become imperative towards reliability, safety and usability. This leads to compromised data quality and, therefore, compromised ethical decision-making based on numerous factors that may stem from the accommodation of ubiquitous computing. More specifically, due to these challenges, the proposed framework incorporates an edge design, AI-based analytics, and a secure communication model. Thinking at the edge results in fast network response without high latency because data processing occurs nearer to the system's edge. Such pre-processing stages such as Anomaly detection, Data imputation and normalization play a crucial role in improving the Usability and reliability of the data in dynamic/Noisy environments.

Security is provided through decentralized data storage thanks to blockchain and end-to-end encryption of the data in question, with reference to the ethical uses of such data. This means that the features of this proposed framework hold out nicely in the actual smart home testbed scenario and they were able to bring out key data quality improvements. Also, premier accomplishments of accuracy, time efficiency and competency conclusively justify the pragmatic usability and applicability of the system. As an example of autonomous data management, virtual assistants are the direction future research will focus on, as systems can automatically maintain compliance with policies at the data level. Another promising approach is federated learning; it is regarded as a mobile edge computing technique on edge devices while at the same time addressing the privacy issue. These developments are critical to cope with and build on the next generation of smart environments, providing better trust, environments, and intelligence in ambient computing environments.

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