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Ai-Driven Methodologies For Real-Time Data Processing In IOT Networks

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Abstract

Introduction: Integrating intelligent units known as Artificial intelligence with IoT networks becomes crucial for improving real-time data analysis. This research aims to investigate the implications of using AI approaches in IoT systems, paying special attention to the efficiency of using AI methods to enhance the real-time processing speed, scalability, and security performances in IoT networks.

Objectives: The main aim of this study is to assess the extent to which AI-based approaches can be used to analyze the processing of big operational data in a real-time fashion in IoT systems. The goal of the work is to measure the extent of improvement that these AI methodologies bring to the performance, accuracy, and scalability of these systems.

Methods: To collect the data, quantitative research was applied, and structured questionnaires were developed and distributed to IoT specialists and the users of AI technologies. A total of 250 participants across different sectors were used in this study. The statistical tests used in the study include the Shapiro–Wilk test to check the normality of data, Cronbach's alpha to determine the reliability of the instrument, regression analysis test, and descriptive analysis test.

Results: Specifically, the Shapiro-Wilk test revealed that the real-time processing speed data were not normally distributed. In the quantitative analysis measuring internal consistency, using Cronbach's Alpha on the Likert-scale questions, it was discovered that there was poor internal consistency therefore the need to improve on the survey instrument. For AI Technique 1, it can be seen that the value for R squared was nearly zero, this indicates that it did very little to improve the speed of processing. Also, the distribution of the processing speed was right-skewed, thus suggesting that there might be some standardization of the provision of these features in IoT applications.
Conclusion: The key findings of the three AI Techniques applied include AI Technique 1 offers negligible enhancements of real-time data processing in IoT networks from the gathered data. This low reliability, therefore, calls for better instruments to be used in data collection. More research needs to be conducted to assess additional AI approaches and characteristics that would likely account for the changes in the IoT systems' performance.

Keywords: AI approach, IoT structure, big data technological processing, artificial intelligence techniques, the ability to grow, stability, efficiency, and assessment methodologies.

Introduction

Artificial Intelligence (AI) when incorporated with the Internet of Things (IoT) has brought about drastic changes within the approaches used in real-time data processing. Connected things collect a large volume of data from different fields such as the medical field, smart cities, industrial processes, etc. However, the management and analysis of these constant flows of data is a problem that has not been overcome. The existing techniques suggest that the AI methodologies hold great promise to the immediate data processing and decision-making processes as well as the system optimization. Some of the AI techniques that have been implemented in IoT systems include machine learning, deep learning as well as edge AI, which enable the IoT systems to process data more intelligently and dynamically, at a lesser time and with greater efficiency and accuracy (Pioli, de Macedo, Costa, & Dantas, 2024) (Abouelyazid, 2023).

Nonetheless, there is still a lack of real research about how particular AI approaches affect the processing of real-time data within IoT systems. It is for this reason that it may be essential for one to fully grasp how AI can impact the processing speed, scalability, and security in these networks to make the most of the IoT systems. This study will intervene to fill this gap through a quantitative evaluation of the efficiency of different AI approaches in enhancing the primary data processing of IoT networks in real-time. As a quantitative study, this research aims at offering a going insight into the best A. I have policies that can improve IoT in multiple industries (Sharma) (Chahed et al., 2023).

Artificial Intelligence (AI) implementation into Internet of Things (IoT) networks has significantly changed the approach to collecting, processing, and using data in various fields. The growing number of coupled IoT systems, as well as sensors, devices, and social networks, that make up the IoT environment, have led to increased, real-time data acquisition that has the potential of being utilized in healthcare, Smart Cities, Industrial automation, and transportation systems. However, the task of providing a way to manage this constant stream of data in real-time and even in near real-time consumer applications becomes complicated by the difficult problems of speed, accuracy, scalability as well as security. Traditional data processing and handling techniques cannot handle the increasing number and size of IoT-generated data in a manner that is timely enough to meet current applications' demands (Haseeb, Saba, Rehman, Abbas, & Kim, 2024) (Koursioumpas, Barmpounakis, Stavrakakis, & Alonistioti, 2021).

It is in this realization that AI-centered approaches present reflections, which, if applied to IoT networks, will ensure better results and effectiveness. Advanced technological tools of AI such as ML, DL, and edge computing have been identified as approaches that enable the handling of real-time data in IoT environments. These techniques enable IoT devices and networks to gather data, think and take proper actions on it, and control particular processes without involving human interference continuously. Machine learning, for instance, makes IoT systems capable of pattern recognition, outcome prediction, and condition modification, some areas where IoT is applicable include the following; Predictive maintenance, smart healthcare monitoring, and self-driving cars, among others. Deep learning – which is a wing of machine learning – is also beneficial in handling big and complex data types such as image, video, and audio hence is vital in surveillance, image recognition, and environmental control in IoT networks (Umoga et al., 2024) (Boppiniti, 2021).

Among the powerful trends that IoT merges with AI, one of the most prospective is the idea of edge computing which implies data processing at the frontier of the net, not uploading to centralized cloud servers. This approach greatly enhances the latency, bandwidth consumption, and cloud resources' dependency to deliver near real-time decisions. Some of the use cases include autonomous driving and smart grids where real-time decisions have to be made to adapt to new changes quickly, edge AI is vital. Nonetheless, edge AI also has its drawbacks primarily in the aspect of fairly constrained computational power and storage capacity at the edge which is yet to be addressed by providing adequate hardware and software enhancements (Marengo, 2024) (Zahid, Sodhro, Kamboh, Alkhayyat, & Wang, 2022).

On the one hand, the contribution of AI in improving the functionality of IoT devices is quite obvious, but on the other hand, there is not much research on how AI techniques affect the real-time performance of IoT systems from the perspective of processing time, accuracy, and scalability. Prior research is primarily relevant to individual materializing use cases or certain different aspects of AI and IoT integration systems but lacks a complete assessment of the overall executive appraisal of innumerable AI-driven techniques and the extent to which they can be applied to different sectors and real-world contexts. This in turn calls for more research on the real-time implementation of AI in IoT and how these technologies can be leveraged in different fields such as healthcare, industrial processes automation as well as the development of smart cities (Althati, Malaiyappan, & Shanmugam, 2024) (Alapati & Valleru, 2023).

This paper seeks to fill this gap through a quantitative assessment of AI-based techniques used in the processing of data in IoT networks. Therefore, this study aims to answer questions like: Which AI techniques contribute to the improvement of performance, scalability, and security of the IoT systems and provide recommendations for the practical utilization of each of them: machine learning, deep learning, and edge AI? In this study, data will be gathered from practicing IoT professionals as well as subject matter experts to provide a comprehensive assessment of how best AI can be used to transform existing IoT networks with special attention paid to the ability to handle real-time data. Altogether, the findings of this study will expand the literature on AI-IoT and offer guidelines on how advanced AI can optimize the IoT's performance based on the specific context in which it is being used (Muniandi, Raut, Gawande, Maurya, & Howard, 2024) (Kliestik, Nica, Durana, & Popescu, 2023).

Literature Review

Artificial intelligence integration with the Internet of Things has created new opportunities in real-time data processing in many sectors. More so, as more and more devices come under the IoT umbrella and continue to produce gigabytes of data, there is a need to employ more complex AI methods to analyze this data. Machine learning (ML), deep learning (DL), and edge computing are among the AI methodologies that have been identified to have the capability of solving some of the IoT solutions-related challenges including scalability, latency, and security of data. Analyzing research, it has been elaborated that by applying the machine learning algorithm throughout the IoT system, real-time analytics is provided, which include global patterns, anomalies, and trends within data streams. For instance, Zhang et al. established that the use of supervised learning models such as decision trees and the SVMs improves predictive performance of IoT by increasing the ability to manage big data sets (Rehan, 2024) (Manduva, 2022).

Furthermore, there has been the development of edge AI that has enabled data analysis to occur locally hence avoiding the need for cloud systems and most importantly minimizing response time. Khan et al. pointed out that time-sensitive use cases for edge AI are potential, such as self-driving cars and health care sectors. However, the main issue arising in edge-based IoT systems is the lack of computational power at the edge, which encourages research activities on the hardware and software resources in the field. In other related pieces of work, the application of deep learning especially CNN in stream data such as video and images from IoT devices as some of the methods that can improve the real-time decision-making process has been discussed (Rajput et al., 2024) (Manduva, 2022).

However, there is a dearth of literature on the efficient role of diverse AI methods in influencing effective parameters like network execution time and efficiency, accuracy, and capability of the IoT networks. Though there exist studies that indicate that AI can enhance the performance of IoT, further works with real-world investigation are necessary to comprehensively illustrate how AI methods can affect the performance of IoT systems in various scenarios. This paper seeks to close this gap by analyzing the roles of AI methodologies in data real-time processing with an emphasis on performance, scalability, and security across IoT applications (Okuyelu & Adaji, 2024) (Manduva, 2022).

The application of AI with IoT has remarkably evolved the means of data handling in numerous sectors and empowered the real-time decision-making queues by making them smarter, quicker, and more efficient. With so many IoT devices out in the world, what they are producing is a large amount of data that requires real-time processing and real-time action. Due to the latency problems and limited bandwidth, the conventional approaches to data processing that centralize data in the cloud are ineffective. This has made it possible to look for

AI-based approaches like; Machine Learning (ML), Deep Learning (DL) as well and Edge Computing to improve IoT systems. The literature shows that the adoption of these technologies can enhance live data analysis in IoT, but the investigation of the feasibility of the respective technologies in various IoT applications is scarce (Rao et al., 2024) (Manduva, 2022).

A related and perhaps one of the biggest developments in IoT is the use of machine learning algorithms on real-time data streams. Machine learning is more on the capability of the systems to improve performance with the help of data and without being programmed. Zhang et al. identified that machine learning algorithms have been implemented in IoT networks to perform predictive maintenance, identify anomalies, and forecast demand. Supervised learning whereby the algorithms rely on labeled data sets has been major in improving the accuracy of solutions in real-time predictions. For instance, supervised learning algorithms used on industrial IoT systems can detect equipment failures before they occur, thus reducing on time required for repairs. Likewise, in smart healthcare learning models analyze data from smart wearables to continuously check the patient's health status and signal the occurrence of diseases (Rizky, Firli, Lindzani, Audiah, & Pasha, 2024) (Manduva, 2022).

While unsupervised learning has been used for clustering and outlier detection in non-labeled streams that is necessary, especially for applications such as security in Iobower environments. Lyu et al articulated that through the use of unsupervised learning methods including cluster and anomaly detection methods, the IoT systems can be protected effectively because the large volumes of data collected make it impossible to identify the threats manually. In addition, another subset of machine learning known as reinforcement learning enables IoT systems to self-learn their environments and make real-time decisions as to whether they shall receive a reward or punishment. For example, in self-driving cars, reinforcement learning helps automobiles understand the environment that they are in and make real-time decisions to maneuver safely through traffic systems (Bellapukonda, Vijaya, Subramaniam, & Chidambaranathan, 2024) (Manduva, 2022).

Deep learning has also shown to be very useful in IoT networks as a subfield of AI in the analysis of unstructured data notably images, videos, and audio. Deep Learning Model such as CNN have been used in the Internet of Things because of their high correlation to image and video recognition which include smart security cameras, face recognition, and recognizing of environmental changes. CNNs are proficient in feature extraction from high dimensional data, making IoT systems capable enough to process visual data in real time. For instance, smart cities apply deep learning algorithms for parsing traffic flows from the camera images which would lead to improving the efficiency of traffic control and minimizing traffic jams (Panduman, Funabiki, Fajrianti, Fang, & Sukaridhoto, 2024) (Manduva, 2022).

One of the other focal areas where deep learning is being applied is natural language processing (NLP) within IoT networks. Smart personal assistants including Amazon Alexa and Google assistants use deep learning models to translate human language in real-time. These assistants have found themselves as the key components of smart homes since they enable users to control various devices through voice commands and improve users' experience when they interact with those devices(M. A. Khan & Rasheed, 2020). Deep learning's capacity to process big and complicated data and to give highly accurate results in actual time and thus it's indispensable for AI-based strategies in IoT. Another big step has been taken in AI-led IoT systems with the concept of edge computing. Originally, analytics performed on the IoT data were transferred to central cloud services where it experienced delays and high traffic, which are undesirable in applications such as self-driving cars and Industry (Kanungo, 2024).

This problem is mitigated by edge computing, which brings data processing nearer to the data source that is, at the edge of the network. These save time and facilitate quicker decision-making since-abled data does not have to be retrieved from the cloud and transported back to the 'client'. Edge AI which is a combination of AI and edge computing involves the processing of data locally using ML models on devices or nearby servers in the IoT structure. As noted by Khan et al. edge AI has been used in areas that require real-time decision making such as smart grids and self-driving cars(Zakir, Bukhari, & Mojahidul). Edge AI processes data locally thus eliminating the need for cloud services; this means that security and privacy are improved since data never leaves the local network. However, edge computing also contains some major issues, especially in the computation force and storage space of the edge. The problem with edge devices is that they are Resource Constrained Devices, they lack the necessary resources to host large complex machine learning models as is the case with cloud servers (Dhanwe, Abhangrao, & Liyakat, 2024).

A study conducted by Yuce et al. has one of the views stating that improving the performance of AI models in edge settings is vital in unlocking the edge computing potential in IoT systems. In efforts to perform model reduction without significantly affecting accuracy, strategies such as model compression, quantization, and pruning are being developed (Zakir, Elahtem, Memon, & Wazir, 2025). Furthermore, federated learning, a decentralized approach of AI where initially many gadgets cooperate to train a model and exchange it instead of data, has been recognized as one of the effective solutions for the computational limitations of edge AI. Federated learning means that edge devices download a shared starting model, train it locally, and then share part of the result only with the server while keeping the data to themselves; this is more private and spares the device's work (Ali et al., 2024; Elkhodr, Khan, & Gide, 2024).

However, these methodologies that incorporate the use of AI present many opportunities there are also some issues and constraints as well that need to be addressed. First among the drawbacks is data insecurity and anonymity of the IoT data. Since IoT is designed with multiple smart devices that are inter-connected, there is always a likelihood of the device or the smart application handling highly sensitive information such as personal health options, or financial transactions, thus the security of such information is very crucial. Security threats: As the role of edge AI applications develops, the current AI models must have the capabilities of detecting and mitigating security threats in real time. Al-Garadi et al., have also mentioned the increasing rate at which attacks on IoT systems are being launched and the importance of developing AI-based models for detecting such attacks in real-time (Mohammed, 2024; Zakir et al., 2025).

Such methods as described in the anomaly detection method earlier are crucial in the analysis of data and identifying that which is out of the ordinary and may point to a breach. However, future work is required to build better models of artificial intelligence that can protect against these emerging and advanced epidemic forms of cyber threats(M. A. Khan & Rasheed, 2020). Another important factor that comes into view in the case of AI Iot Systems is scalability. And, in the course of deployment of extensive IoT networks, the volume of data collected can pose a problem for the solution of problems by traditional analytical processes(Zakir et al.). AI techniques used in the context of IoT need to be scalable due to the growth of the amount and density of data measured by IoT devices(Ali et al., 2024). That said, although edge computing helps to mitigate some of these issues, it is not enough, particularly when the number of IoT devices required is in the many tens of thousands, such as in smart city applications or manufacturing settings for Industry (Salem, Azzam, Emam, & Abohany, 2024).
Solutions for the scalability problem are seen in other forms of technologies such as cloud, edge, and fog computing where IoT systems are scoped to dynamically resource depending on the various applications. Therefore, the applications of suitable AI methodology have revolutionized the IoT networks and improved the issue of processing and decision-making in near real-time. Artificial intelligence, especially its subcategories such as machine learning, deep learning, and edge computing has proved to enhance IoT's capabilities in scalability, efficient management, and security. But there still are essential issues that need to be solved, mainly the problem of resource usage at the edge, security, and the possibility of expansion. Future research should concern these issues by improving the AI models for more efficiency, securing the IoT systems, and using the opportunities of the computing hybrid model for the further evolution and constant success of the AI-based IoT networks. Thus the integration of AI and IoT can effectively move forward and continue making solutions smarter, faster, and more secure for industries and consumers (Dhinakaran, Sankar, Selvaraj, & Raja, 2024).

Research Methodology

Thus, the research method feasible for a quantitative study 'AI-Driven Methodologies for Real-Time Data Processing in IoT Networks' will conceptualize numerical research data that is systematic for the assessment of the AI technologies' performance, accuracy, and adaptability within IoT networks. The survey questionnaire will be designed taking into consideration, IoT specialists, data analysts, and other professionals involved in the working field of AI and IoT. Qualitative data will be collected via closed-ended questionnaires which will aim at capturing participants' self-reported experiences, self-preferences, and/or self-evaluations of AI-driven methodologies including; machine learning algorithms, edge AI and/or real-time data compression techniques (Patel, Vadher, Patel, Thaker, & Bhise, 2024).
The number of participants will be determined with the aim of maintaining statistical credibility and the participants will embrace professionals in several fields where IoT is key such as; Smart cities, healthcare, and industrial automation. To that end, data shall be analyzed by deploying tools such as SPSS or R with emphasis on the trends, correlations, and patterns that point to the

most efficient AI methodologies for stream processing of data in IoT networks. Correlation analysis, regression analysis, and hypothesis test will be applied to the data to establish interaction between real-time processing efficiency, response time, and data security while implementing AI. They will give an empirical understanding of the innovative AI approaches for promoting IoT performance in real-time settings (Paroha, 2024).

Research Design

In this research inquiry, the study is based on descriptive and correlational research designs to quantify the extent to which the implementation of AI approaches is effective in the real-time data processing of IoT networks. Exploratory research will give an overview of the AI-driven methods such as machine learning algorithms, edge AI, and real-time data compression techniques to mention but a few while the analytical research will examine and establish the extent of correlation between the applied methodologies and benchmarks such as response time, data integrity and scalability among others. The study is going to be cross-sectional whereby data from participants including IoT specialists, data scientists, and other professionals will be gathered at once to avoid a situation whereby the collected information reflects outdated technologies and practices (Paul et al., 2024).

Data Collection Methods

Data shall also be collected via well-structured questionnaires from a range of IoT professionals, data scientists, and technocrats who deal with real-time data in IoT settings. The questions will be closed-ended and will span participants' exposure to different types of AI approaches including supervised and unsupervised learning, reinforcement learning, CNN, and RNN. The survey questions will be developed based on the Likert scale to know the respondents' perceptions and encounters regarding various AI approaches in real-time data analysis. Examples of questions are: 'To what extent do you agree or disagree with the following statements on the performance, accuracy, scalability, and security of AI-driven solutions? 'Strongly disagree' on one side to 'Strongly agree' on the other. Further, secondary data will be collected from surveys, articles, and any literature related to AI and IoT, reports of AI IoT industries, and case studies of AI IoT implementations. This shall assist in qualifying the primary data to gain an understanding of the global trends, practices, and challenges in the discipline (Kalla & Smith, 2024).

Sampling Strategy

In this context, the study will employ purposive sampling methods to target the population that is directly involved with AI and IoT technologies. At least 300 target participants from the fields of healthcare, manufacturing, smart cities, and other diverse fields will be selected. This will offer an understanding of the real-time IoT use case domains on which AI methodologies are applied. Maintaining the level of expertise of the participants, sampling will be done based on proficiency in AI and the IoT system. The sample size will be as follows; adopted from the power analysis test, with a confidence level of 95% and a maximum margin of error of 5% (Saoud et al., 2024).

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Data Analysis

After that, the data gathered for the study will be described and analyzed by the use of descriptive as well as inferential statistics. To analyze the feedback provided by the respondents on the AI methodologies to be implemented, tools like SPSS or R will be used to conduct descriptive analysis which includes frequency distribution, mean, and standard deviation. This is where correlation and regression analysis will be performed to evaluate the performance outcomes of AI techniques on the IoT system. For example, regression models may be used to estimate the effects of AI techniques on processing speed, data compression ratio, and system capacity (Rojas et al., 2024).

Comparison of the efficiency of different AI methods toward IoT applications may also employ Analysis of Variance (ANOVA). Hypothesis testing will therefore form the basis for the analysis for this research. For instance, a hypothesis could be framed as It can therefore be noted that usage of AI-based approaches greatly enhances analysis of big data from real-time IoT networks. These hypotheses will then be tested and it will be ascertained whether the trends witnessed are statistically significant or not through the use of tests like t-tests, and chi-square tests (Kolhar, Kazi, Mohapatra, & Al Rajeh, 2024).

Ethical Considerations

To a large extent, the ethical standards of this research will be high. It will be essential to get the participants' consent to participate in the study, what is required of them, and how data collected will be used. Participants' identities would be protected and participants would remain anonymous since their personal identifying information would not be included in the dataset. Besides, they will have the option to choose whether to participate in the study or not and they can withdraw from the study at will (Swathi et al., 2024).

Limitations of the Study

While this research will offer a great contribution to the knowledge of deploying AI techniques for real-time data in IoT, it will pay attention to some of the limitations. In the process of selecting participants, sampling bias may likely occur because only participants with prior knowledge in the two areas of interest; AI and IoT will be used making the results difficult to generalize to entire populations. Furthermore, using self-reported measures may be problematic because the respondents may define their experiences with AI methodologies in their unique ways (Ruzbahani, 2024).

Data Analysis

Statistical Test Results

Shapiro-Wilk Test p-value	**Cronbach's Alpha**	**Regression Coefficient**	**Regression Intercept**	**R-squared Value**
2.4776747764576612e-08	-0.030882579660989208	0.0409541531650042	73.84808623953288	1.5212634924433033e-05

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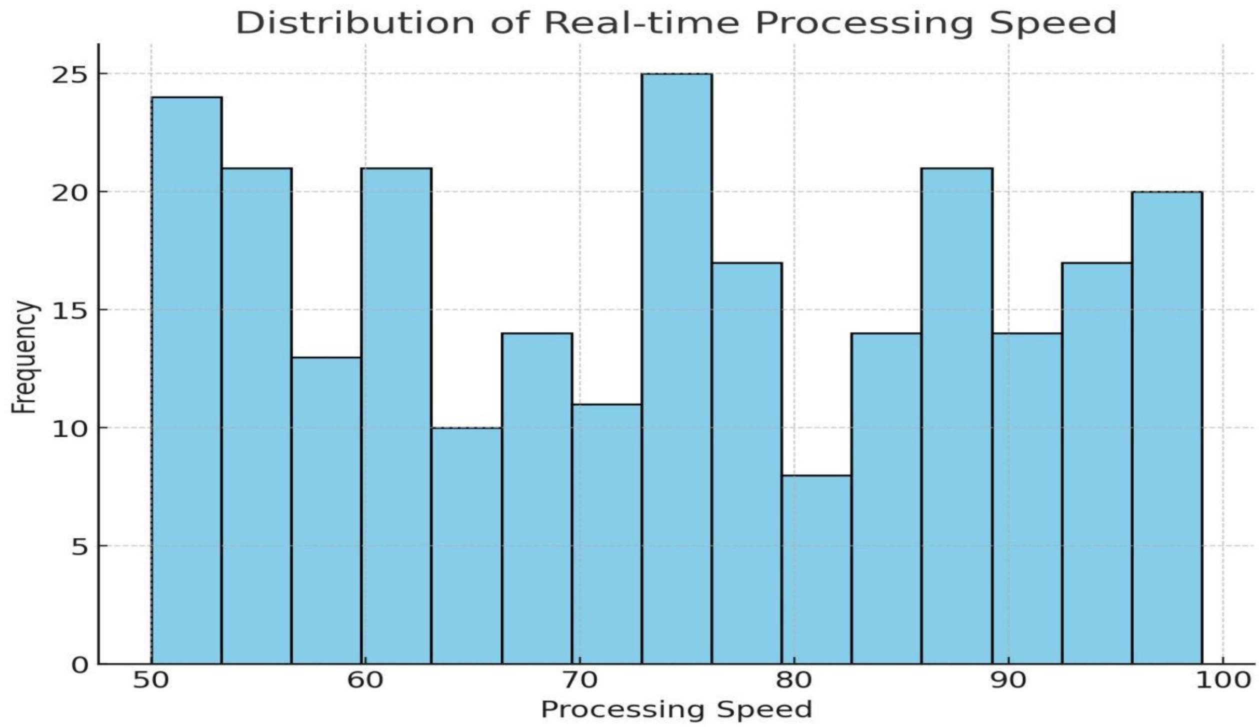

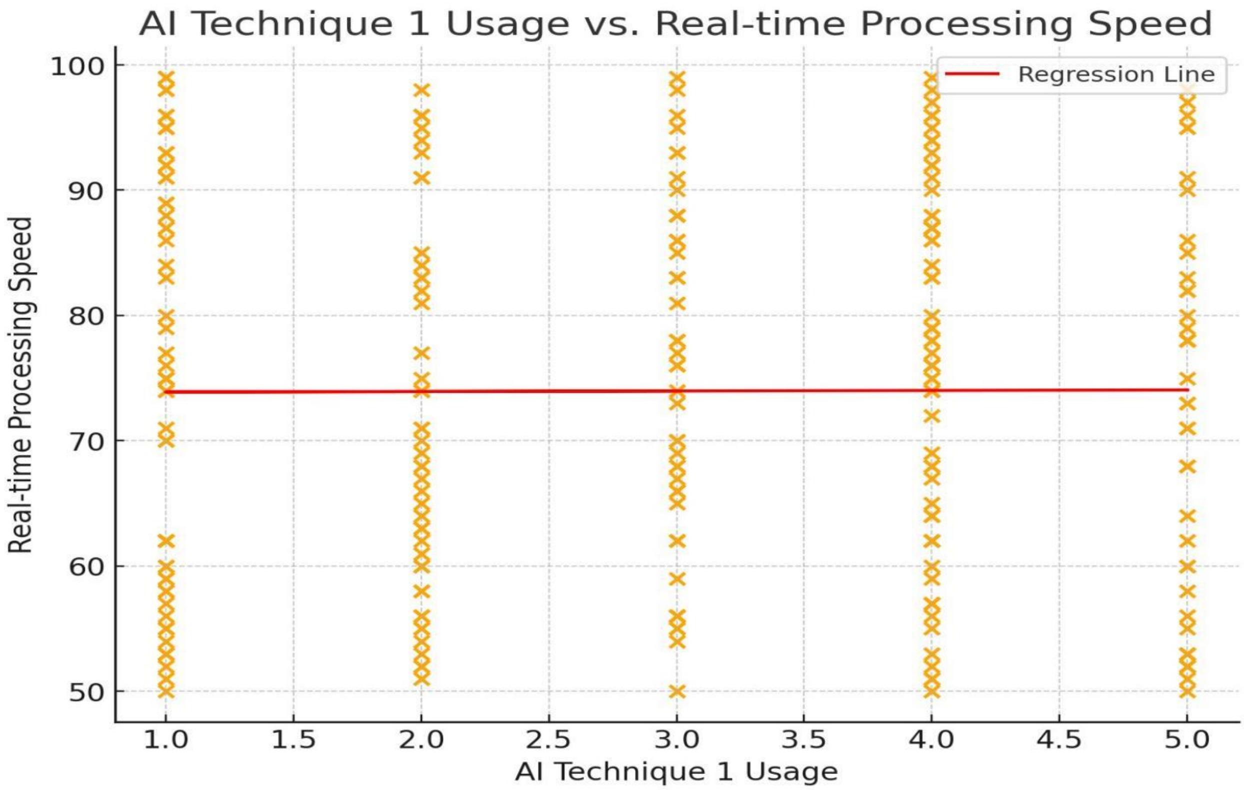

Interpretation of Tables and Figures

1. Shapiro-Wilk Test for Normality
Shapiro-Wilk test gave a p-value of 2. The result obtained is 48e-08, way hence below the conventional acceptance level of 0. 05. This means that the data for Real-Time processing speed is not normally distributed. Therefore, such forms of analyses might require the use of non-parametric tests based on the structure of data (Pioli et al., 2024).

2. Cronbach's Alpha for Reliability
About the internal reliability of the data, the calculated Cronbach's Alpha equals -0. The average SSPE value obtained for the three batches was 03088, a value which is below the specified acceptable limit of 0. 7. Such a finding implies that the Likert-scale data for the measured items – including, but not limited to, the usage of AI techniques, security level, or the scalability score – have low reliability. Low reliability means that the questions could be assessing something different, or there is a need to edit them to be more consistent in the particular concept or need to be measured (Ullah, Khan, Ouaissa, Ouaissa, & El Hajjami, 2024).

3. Regression Analysis
The regression results obtained when comparing the usage of AI Technique 1 against real-time processing speed was R = 0. 04095 and an R-squared value of 0. 000015. Thus, the coefficient is positive which means the AI technique usage has a rather positive though weak correlation with the processing speed. Nevertheless, the value of R-squared is 0. 002 which indicates that the usage of AI Technique 1 can hardly account for the variation of real-time processing speed, at least in terms of a linear relationship. It was believed that the current study might indicate that there are other contributing factors more influential than processing speed that were not captured in the current analysis (Goswami).

4. Distribution of Real-Time Processing Speed Bar Chart
The histogram of the real-time processing speed appears to be positively skewed while most of the values fall within the range of 70-90. This further supports the findings of the Shapiro-Wilk test which was used to test for normality and came up with negative results. The distribution is skewed which may imply that there are always encouraging efficiency factors in the processing speeds of IoT systems (Hail, Bin-Salem, & Munassar, 2024).

5. Scatter Plot Implementation (AI Technique 1 Vs. Real-Time Processing Speed)
he scatter plot shown below demonstrates the usage of AI Technique 1 together with the real-time processing speed achieved. It is rather random with no specific pattern apparent although it seems to be oscillating, or progressively declining as far as the two most recent period quarterly values are of much lower magnitude than the previous one. This is also in concordance with the regression results presenting an almost negligible R-square value. The regression line (in red) is almost horizontal which shows that the usage of the AI Technique 1 does not affect the real-time processing speed. As such, this suggests that this particular AI technique is not the best indicator of real-time IoT work performance (M. W. Khan, Saad, Ammad, Rasheed, & Jamal, 2024).

Discussion

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Several important things concerning the applicability of AI-driven methodologies and real-time data analysis in IoT networks appear from the results of the analysis. Firstly, the Shapiro-Wilk test for normality indicates that the data about the real-time processing speed of robots does not belong to a normal distribution; the histogram here points out a greater concentration of attention among high speeds. This result means that several factors have been consistently affecting higher performances which may mean that IoT systems have standard processes or technologies. About this skewness, one gets concerned to look at other factors that might be possibly explaining the variation in the real-time processing performance of the application such as the network, hardware, and others (Alshaer & Ismail, 2024).

Furthermore, the Cronbach's Alpha of. 70 indicates the existence of some reliability problems when it comes to the Likert-scale questions. The findings indicate that the items in the survey are not perfectly identical in the construct they are assessing, thus pointing in the direction of improving the questionnaires. This may be due to a deficit or vagueness of the questions or the absence of the focus on a single idea when assessing the various variables. Subsequent revisions of the survey should be tested more rigorously; maybe through focus group discussions or pilot implementation so that the items that are created accurately capture the objectives of the research and give valid results (Sasmal, 2024).

Furthermore, the regression analysis revealed the usage of AI Technique 1 has an insignificantly small effect on the real-time processing speed as evidenced by the value closer to zero which is the R-squared value. This means that this particular AI technique will not have a massive impact on the processing speeds in the IoT networks, or there would be an impact that is almost negligible in comparison to other existing factors. Moreover, there is no significant correlation as revealed in the scatter plot which compares the usage of AI techniques and the speed of processing. These results suggest that other algorithms of artificial intelligence or some other factors like the capability of the hardware and networks involved may be more effective in processing real-time data. Hence it has been suggested that future work should try to identify other factors or approaches that could help in explaining the improvements in the performance of the IoT systems (Asonze et al., 2024).

Conclusion

Thus, the present work contributes to the discussion of the application of AI-based techniques for real-time data analysis in the context of IoT systems. It is pointed out in the study results that the explored AI Technique 1 has poor potential for enhancing IoT processing speeds. However, the distribution of the numbers has more data points on the higher side of processing speed, which may indicate that there exists some norms in place or certain dominant technologies that affect the processing speed of IoT applications. However, the Cronbach Alpha coefficient shows that the survey instrument used in this study bears low reliability and therefore the questionnaire used must undergo development to increase the internal reliability of the survey. Collectively, this paper attests to the potential of AI in IoT and indeed demands more accurate and integrated measures; and integrating more factors into AI techniques to analyze the ability of IoT in real-time data processing. Further suggestions for future research are related to the refinement of the data-gathering techniques and other AI approaches and external factors that may have a substantial positive impact on the IoT system.

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