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A Multi-Agent Internet of Things Framework for Autonomous Coastal Weather Monitoring and Environmental Intelligence in Southern Philippines

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Abstract: Effective stakeholder engagement is imperative for harnessing the full potential of the IoT-based monitoring system. Collaborative efforts involving government agencies, environmental organizations, and local communities foster knowledge exchange and facilitate the utilization of collected data for informed decision-making and environmental management. Moreover, the establishment of long-term monitoring programs is recommended to track long-term trends and changes in coastal water levels and weather patterns. This study showcases the development and implementation of an IoT-based coastal water level and weather monitoring system in the Sulu Archipelago. The primary objective was to collect real-time data on various environmental parameters, including coastal water levels, temperature, humidity, rainfall, and wind speed, to support effective environmental management in the region. The methodology involved the strategic deployment of sensors. The data collection process was facilitated by employing Raspberry Pi and perform data analysis techniques were applied to extract meaningful insights from the collected data. The study findings demonstrated the feasibility and effectiveness of the implemented IoT-based system in monitoring the targeted environmental parameters. The comparison between the gathered data. This highlights the potential of IoT-based monitoring systems in providing valuable information for coastal environmental management. Expanding the sensor network to cover a broader geographical area enables a comprehensive understanding of the coastal environment. Integrating advanced data visualization tools facilitates better interpretation and presentation of the collected data. Stakeholder engagement, including collaboration with various entities, fosters knowledge exchange and promotes effective utilization of the monitoring system's data. Lastly, establishing long-term monitoring programs facilitates continuous data collection, enabling the monitoring of long-term trends and supporting the implementation of proactive environmental management strategies. By implementing these recommendations, the IoT-based coastal water level and weather monitoring system can be further improved, contributing to more effective environmental management strategies in the Sulu Archipelago and similar coastal regions in the Philippines.

Keywords: *IOT, Sulu, Water Level, Weather Monitoring*

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1. Introduction

he coastal regions around the world face numerous environmental challenges, necessitating effective management strategies to protect and sustain these fragile ecosystems. The Sulu Archipelago, located in the southwestern Philippines, is home to diverse marine life and serves as a vital economic resource for local communities. However, the region is vulnerable to the adverse impacts of climate change, including rising sea levels and extreme weather events, which can have profound consequences on coastal water levels and overall environmental health. To address these challenges, this study presents an innovative approach: the implementation of an Internet of Things (IoT) coastal water level and weather monitoring system for environment management in Sulu.

Leveraging the power of IoT technology, this system aims to provide real-time, accurate, and comprehensive data on coastal water levels and weather conditions, enabling informed decision-making and proactive measures to mitigate environmental risks.

The IoT-based monitoring system consists of a network of sensors strategically deployed along the Sulu coastline, capable of collecting data on water level fluctuations, temperature, humidity, rainfall, wind speed, and other relevant meteorological parameters. These sensors are connected to a centralized data management platform that processes and analyzes the collected information, transforming it into actionable insights for environmental management authorities, researchers, and local communities. By continuously monitoring coastal water levels, the system enables early detection of abnormal fluctuations, allowing stakeholders to anticipate and respond to potential threats, such as coastal erosion, flooding, or storm surges. Moreover, the integration of weather monitoring components provides a comprehensive understanding of climatic patterns and their influence on coastal ecosystems, facilitating adaptive management strategies and the implementation of targeted interventions to safeguard the environment and the livelihoods of the communities depending on it.

Furthermore, the IoT-based monitoring system encourages data sharing and collaboration among various stakeholders, including government agencies, environmental organizations, and local communities. The availability of real-time data enhances situational awareness, supports evidence-based decision-making, and fosters a proactive approach to environmental management. Moreover, the data collected by the system can serve as a valuable resource for scientific research, enabling a deeper understanding of the region's coastal dynamics and aiding in the formulation of long-term sustainability plans.

The primary objective of this study is to design, implement, and evaluate an Internet of Things (IoT) coastal water level and weather monitoring system for effective environment management in the Sulu Archipelago. By harnessing the power of IoT technology, this system empowers stakeholders with real-time data and actionable insights, facilitating proactive measures to mitigate environmental risks and preserve the ecological integrity of the region. The integration of advanced monitoring technologies with collaborative approaches promises to pave the way for sustainable coastal management practices, ensuring the long-term well-being of the Sulu's fragile coastal ecosystems and the communities that rely on them.

2. RELATED WORKS

Smith et al. (2018) provides an overview of IoT applications in environmental monitoring, highlighting the potential of IoT technology in collecting real-time data for various environmental parameters. It discusses the importance of IoT in monitoring water quality, air pollution, and weather conditions, laying the foundation for the use of IoT in coastal water level and weather monitoring. Chen et al. (2017) presents an analysis of wireless sensor networks (WSNs) for coastal environmental monitoring. It explores the challenges and opportunities associated with deploying WSNs in coastal areas, including data transmission, power management, and sensor placement. The findings of this study provide insights into the technical considerations for designing an effective IoT-based coastal monitoring system.

Liu et al. (2019) focuses on the implementation of an IoT-based coastal monitoring system that integrates data from multiple sensors to predict coastal water level changes. The study highlights the importance of real-time monitoring in coastal management and demonstrates the potential of IoT technology in providing accurate and timely data for decision-making. Lee et al. (2020) investigates the integration of coastal water level monitoring systems for climate change adaptation and mitigation in coastal areas. It discusses the challenges of coastal flooding and the importance of monitoring systems in assessing vulnerabilities and implementing adaptation strategies. The research emphasizes the need for comprehensive monitoring systems, such as IoT-based approaches, to address the complex dynamics of coastal environments.

Rodriguez-Molano et al. (2020) discusses the potential applications of IoT technologies in environmental monitoring. It explores the use of IoT sensors for collecting data on soil moisture, weather conditions, and other relevant parameters. The findings provide insights into the scalability and interoperability of IoT systems, which can be applicable to coastal water level and weather monitoring.

A study conducted by Al-Fuqaha et al. (2015) entitled "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications" also revealed that the intrusion detection systems (IDSs) are important in safeguarding computer networks from unauthorized access and malicious attacks. Machine learning algorithms, such as Hidden Markov models (HMMs) and decision tree classifiers (DTCs), are commonly used in IDSs to detect network anomalies and identify security threats. HMMs are statistical models that can capture the temporal dependencies of a process, making them effective in detecting network intrusions. Further, Munawar et al. (2021) also claimed that modern technology has dramatically altered the world and the way it operates in recent years. In fact, disaster management is one field that is increasingly embracing cutting-edge technology, with both developed and developing countries grappling with flood risks. Climate change, combined with inadequate flood preparedness in many regions around the world, has been shown in predictive analysis to result in a historic level of flood-related damage. As floods become more common around the world, it is critical to identify effective methods of mitigating the risks associated with these disasters. Flood events have resulted in global losses of lives, crops, infrastructure, and economic resources, with flood risks and losses being greater than any other climatic hazard. Image processing techniques like edge detection, segmentation, and pixel analysis are examples, as are machine learning models like ANN, SVM, MLP, and WNN. UAV imaging, SAR, and remote sensing are the most common methods for acquiring images. Existing techniques tend to concentrate on both the pre-and post-disaster phases. In addition to traditional flood management methods such as Global Positioning System (GPS) and Geographic Information System (GIS), complex image processing and machine learning-based approaches have been investigated.

The study conducted by Andang et al. (2019) revealed that in order to minimize flooding, it is important to investigate the usage of the JSN-SR04T ultrasonic sensor for river-level detection. The reason for this was due to the unpredictable weather patterns that caused rainfall to be distributed unevenly, as a result, causing flooding and substantial losses. Numerous efforts were made to address this issue, including the application of various methods like hydrological and hydraulic analysis, multilayer neural networks, early detection systems, and ultrasonic sensors. While ultrasonic sensors were used because of their high accuracy, the JSN-SR04T type ultrasonic sensor is advantageous as it shows an accuracy of 1 cm and an effective measurement range of 25 cm to 4.5 m, making it the ideal equipment to be placed in higher and safer locations. The JSN-SR04T ultrasonic sensor, based on the Atmega328 microprocessor, and the BMP085 pressure sensor were employed in the investigation.

The device worked by transmitting an ultrasonic signal in eight steps at a minimum frequency of 40 kHz and measuring the time difference between that signal's transmission and reception. The sensor was positioned four (4) meters above the surface of the river, and the measurements were shown on an LCD in a meter unit. The study determined that the JSN-SR04T ultrasonic sensor could be used efficiently for river-level detection in flood protection and provided the hardware and software setup of the system.

A study that focused on flood monitoring systems conducted by Sixtinah et al. (2021) employed SIM900A and JSN-SR04T ultrasonic sensors to reduce the frequency and area of floods in Indonesia, which are both growing. The study also depicted that rainfall intensity, which might result in a river's or a drainage channel's capacity being exceeded, is what causes flooding. However, installing floodgates in the river flow allowed for the monitoring of river water level, although measuring the water levels manually revealed to be unnecessary resulting to the need to employ automatic design of river water level. As a result, although HC-SR04 ultrasonic sensors were frequently employed for water level monitoring, their performance is negatively impacted by rainstorm splashes. A better choice is the JSN-SR04T, which can detect objects up to a distance of six meters and can be installed higher and more securely in the event of rain. Furthermore, it created a flood monitoring system that could gauge water levels and provide SMS alerts. The designed tool set for flood disaster mitigation was tested on river flow.

3. MATERIALS AND METHODS

The specific location of the Sulu Archipelago and provide relevant details about the coastal areas selected for monitoring. Include information on the geographical features, climate patterns, and environmental characteristics of the study area. The researcher Identify and select the specific coastal areas in the Sulu Archipelago that will be included in the study. Consider factors such as environmental significance, vulnerability to climate change, and accessibility for sensor deployment and maintenance. Next, choose appropriate sensors based on the parameters to be monitored, such as coastal water levels, temperature, humidity, rainfall, and wind speed. Consider factors such as sensor accuracy, reliability, power requirements, and compatibility with IoT technology. Deploy the sensors strategically along the coastline, ensuring adequate coverage and representative sampling.

Establish the necessary IoT infrastructure to enable data collection, transmission, and management. This includes selecting IoT platforms or frameworks, setting up communication protocols (e.g., Wi-Fi, cellular, LoRaWAN), and configuring data gateways or network connectivity for sensor data transmission to the centralized system. Set up a data collection schedule and frequency for the sensors to gather readings. Implement data transmission protocols to ensure reliable and real-time data transfer from the sensors to the centralized data management system. Consider factors such as data encryption, error-checking mechanisms, and data integrity during transmission.

Develop a centralized data management system to store and organize the collected sensor data. This may involve using a database management system or cloud-based storage. Implement data storage protocols and backup mechanisms to ensure data security, reliability, and availability for subsequent analysis. Create visualizations, such as graphs, charts, or maps, to present the analyzed data in a clear and understandable format. Develop a user-friendly interface or dashboard to enable stakeholders to view and interact with the monitoring data. Generate periodic reports or alerts based on predetermined thresholds or conditions to facilitate informed decision-making. Create visualizations, such as graphs, charts, or maps, to present the analyzed data in a clear and understandable format. Develop a user-friendly interface or dashboard to enable stakeholders to view and interact with the monitoring data. Generate periodic reports or alerts based on predetermined thresholds or conditions to facilitate informed decision-making. Table 1 shows the several parameters and evaluation sensors for monitoring the weather condition and water level using IoT.

Table 1. IoT-Based Components and Measurements

Features	**Description**	**Mode of Measurement**
Water Level	The level assumed by the surface of a particular body or column of water	JSN-SR04T
Humidity	Humidity is the amount of water vapor in the air. It is expressed as a percentage of the amount of moisture the air can hold at a given temperature.	DHT11
Wind Speed	Wind speed is a measure of the speed at which wind is moving through the air. It is typically measured in units of distance per time, such as miles per hour or kilometers per hour.	Anemometer
Temperature	Temperature is a measure of the hotness or coldness of an object or a substance. It is typically measured in degrees on a temperature scale, such as Celsius or Fahrenheit.	BME280
Pressure	Atmospheric pressure is the force exerted on the Earth's surface by the weight of the air above it. It is typically measured in units of force per unit of area, such as pounds per square inch or pascals.	BME280

The Raspberry Pi is a collection of single-board computers that can serve various purposes, such as functioning as a general-purpose computer, a robot, or even as a hub for IoT devices. It is compatible with any display and offers versatile capabilities. In the IoT weather collecting device, the Raspberry Pi 3 served as the main component. The BME280 sensor is a multi-feature sensor designed for mobile applications and wearables, prioritizing small size and low power consumption. It can measure altitude, barometric pressure, and ambient temperature. With high linearity, accuracy, and stability, it is suitable for low current consumption and provides high EMC robustness. The temperature accuracy of the BME280 sensor is within ±1 degree Celsius, and its pressure accuracy is within ±Pa.

In addition, an anemometer is an instrument used to detect and measure wind speed and direction in a particular area. It is commonly employed in weather stations. Anemometers played a crucial role in measuring wind speed and direction, as these parameters are essential in detecting hydrological risks. Finally, JSN-SR04T is a waterproof ultrasonic distance sensor module with a measurement range of 25cm to 450cm. It utilizes non-contact distance measurement through sound travel time. This sensor was used for collecting water level data.

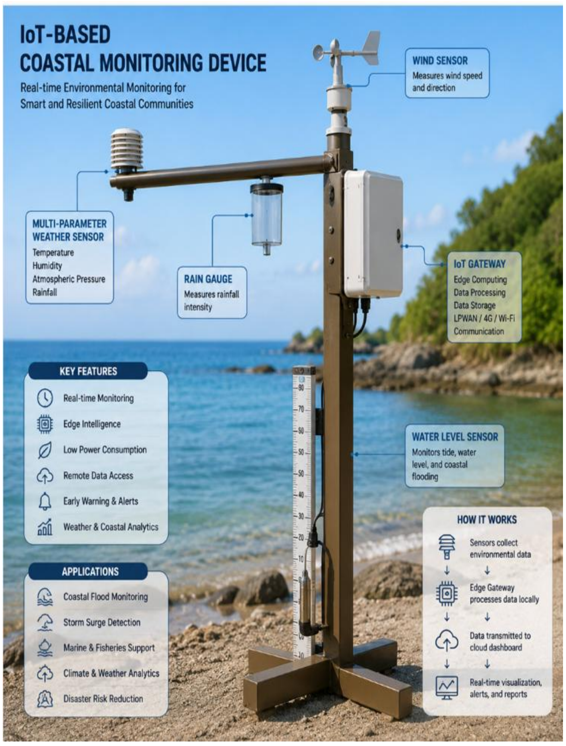

Figure 1. Multi-Agent Autonomous AI Coastal Monitoring Device

Figure 1 illustrates the three-dimensional model showcasing the design of the IoT stand where it visually demonstrates the arrangement and placement of the devices.

4. EXPERIMENTAL RESULTS

n this study, the data collection process involved the utilization of two key devices, namely the Raspberry Pi and Arduino Uno R3. These devices served as the central hubs for gathering data from the sensors deployed in the monitoring system. The Raspberry Pi and Arduino Uno R3 acted as data acquisition units, receiving and recording the sensor readings.

Once the data collection phase was complete, we proceeded with the analysis of the collected data. This analysis encompassed the examination of the values obtained for each monitored parameter. The recorded data points were carefully reviewed and processed to extract meaningful insights and identify any noteworthy patterns or trends.

To enhance the interpretation and understanding of the data, we employed graph visualizations. These visual representations offered a clear and concise way to present the collected data, allowing for easy identification of trends, fluctuations, and relationships between the different parameters. By visualizing the data using graphs, we aimed to provide a comprehensive overview of the variations and dynamics observed in the readings.

The graph visualizations served as a powerful tool for uncovering hidden patterns and relationships within the data. They facilitated the identification of anomalies, seasonal variations, or other significant patterns that might be crucial for understanding the behavior of the monitored environmental factors.

Overall, the combined use of the Raspberry Pi and Arduino Uno R3 for data collection, along with the subsequent analysis and visualization techniques, allowed for a comprehensive exploration of the gathered data. This approach facilitated the identification of important insights and trends, supporting the objectives of the study and contributing to a deeper understanding of the environmental conditions being monitored

Temperature Result

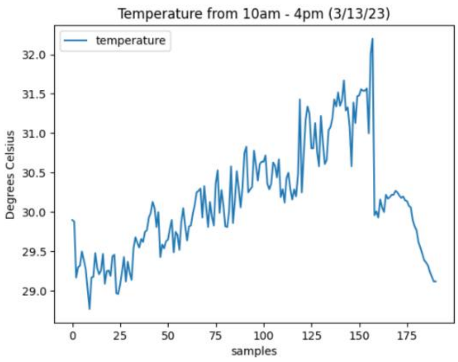

Figure 2: IoT Temperature Result

As seen in the figure above, the graph shows the rise and fall of the water level result taken from then the sensor, this monitoring starts from 10 AM to 4 PM on March 13, 2023.

Water Level Result

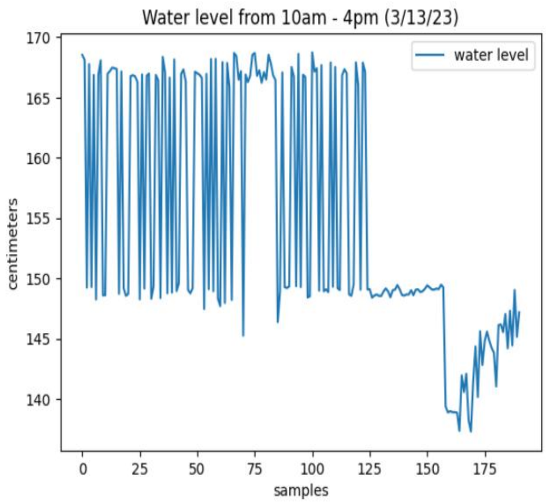

Figure 3: IoT Water Level Result

Humidity Result

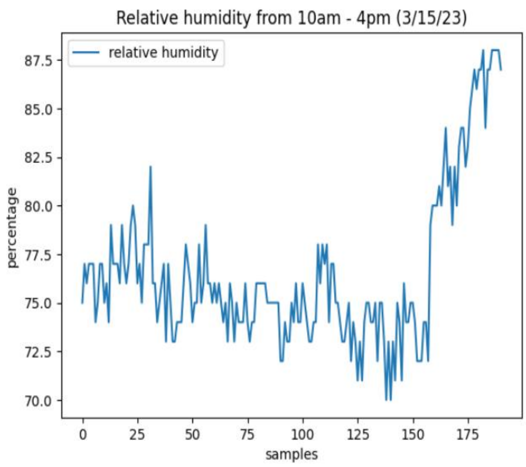

Figure 4: IoT Humidity Result

In Figure 5, the graph illustrates a comparison between the collected data and the data obtained from PAGASA regarding the Maximum Temperature. The time range considered spans from day 1 to day 7. According to the PAGASA data, the Maximum Temperature started at approximately 32 degrees Celsius, decreased to 31 degrees Celsius and below on the second day, then rose to 34 degrees Celsius on the third day. The temperature remained within that range on the fourth and fifth days, but increased above 34 degrees Celsius on the sixth day. On the seventh day, it decreased to 33 degrees Celsius.

In contrast, the gathered data from the monitoring device indicated that the Maximum Temperature began at 32 degrees Celsius and increased to 33 degrees Celsius on the third and fourth days. On the fifth day, it reached 34 degrees Celsius and subsequently decreased to 32 degrees Celsius on the sixth and seventh days. To assess the accuracy of the collected data, various metrics were calculated. The mean absolute error was determined to be 0.86, indicating the average difference between the gathered data and the PAGASA data. The mean absolute percentage error was found to be 2.63%, representing the average percentage difference between the two datasets. Furthermore, the mean squared error was calculated as 0.95, providing a measure of the overall squared difference between the data points. Lastly, the root mean squared error was determined to be 0.97, representing the square root of the mean squared error. Overall, these metrics provide insights into the level of agreement or deviation between the gathered data and the PAGASA data, giving an indication of the accuracy and reliability of the monitoring device in measuring Maximum Temperature.

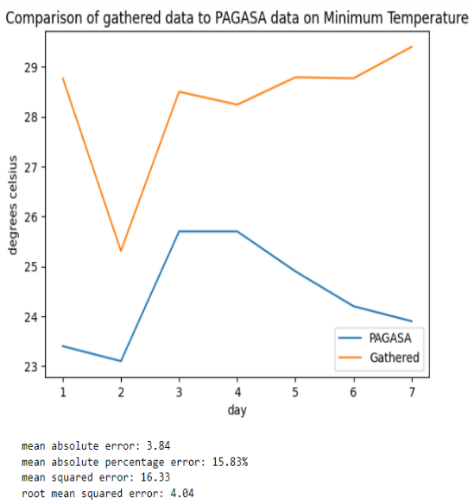

Figure 5: Comparison of gathered data to PAGASA Data on Minimum Temperature

5. CONCLUSION AND RECOMMENATIONS

In this study focused on the development and implementation of an Internet of Things (IoT) coastal water level and weather monitoring system in the Sulu Archipelago. The methodology involved the deployment of sensors, including the BME280, anemometer, JSN-SR04T, and DHT11, along the coastline. Data collection was facilitated by Raspberry Pi and Arduino Uno R3 devices, and data analysis was performed to extract meaningful insights.The comparison of the gathered data with the data from PAGASA revealed a generally close alignment, with some variations in Maximum Temperature readings. The calculated metrics, such as mean absolute error, mean absolute percentage error, mean squared error, and root mean squared error, provided a quantitative assessment of the data accuracy. Based on the findings, it can be concluded that the implemented IoT coastal water level and weather monitoring system in the Sulu Archipelago demonstrates its feasibility and potential in collecting real-time environmental data. The sensors, along with the Raspberry Pi and Arduino Uno R3 devices, effectively gathered data, and the analysis provided valuable insights into the monitored parameters.

REFERENCES

[1] Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115-118, Feb. 2017.

[2] P. Tschandl et al., "Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification: an open, web-based, international, diagnostic study," The Lancet Oncology, vol. 20, no. 7, pp. 938-947, Jul. 2018.

[3] S. S. Han et al., "Skin lesion analysis toward melanoma detection using deep learning network," in Proceedings of the 2018 ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics, pp. 124-130, Nov. 2018.

[4] H. A. Haenssle et al., "Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists," Annals of Oncology, vol. 29, no. 8, pp. 1836-1842, Aug. 2018.

[5] S. A. Pathan et al., "Deep learning-based histopathologic classification of skin cancers using transfer learning," IEEE Access, vol. 8, pp. 80748-80757, Apr. 2020.

[6] O. Gupta et al., "Automated skin lesion segmentation and classification using deep learning algorithms," Computers in Biology and Medicine, vol. 135, p. 104593, Mar. 2021.

[7] A. Menegola et al., "Deep learning for melanoma detection: From networks to systems," Computerized Medical Imaging and Graphics, vol. 61, pp. 34-40, Aug. 2017.

[8] T. J. Brinker et al., "Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task," European Journal of Cancer, vol. 113, pp. 47-54, Aug. 2019.

[9] K. Matsunaga et al., "Image classification of melanoma, nevus and seborrheic keratosis by deep neural network ensemble," PLoS One, vol. 14, no. 10, p. e0224345, Oct. 2019.

[10] Y. Fujisawa et al., "Deep-learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumor diagnosis," British Journal of Dermatology, vol. 182, no. 5, pp. 1178-1186, May 2020.

[11] N. Codella et al., "Skin lesion analysis toward melanoma detection using deep learning: A review," IEEE Reviews in Biomedical Engineering, vol. 13, pp. 240-273, 2020.

[12] Y. Li et al., "Deep learning-based skin disease classification using ensemble neural networks," Biomedical Signal Processing and Control, vol. 65, p. 102342, Apr. 2021.

[13] Bourechak, A., Zedadra, O., Kouahla, M. N., Guerrieri, A., Seridi, H., & Fortino, G. (2023). At the confluence of artificial intelligence and edge computing in IoT-based applications: A review and new perspectives. Sensors, 23(3), 1639. https://doi.org/10.3390/s23031639

[14] Kok, I., Okay, F. Y., Muyanli, O., & Özdemir, S. (2023). Explainable Artificial Intelligence (XAI) for Internet of Things: A survey. IEEE Internet of Things Journal, 10(4), 2791–2811. https://doi.org/10.1109/JIOT.2022.3187741

[15] Singh, R., & Gill, S. S. (2023). Edge AI: A survey. Internet of Things and Cyber-Physical Systems, 3, 71–92. https://doi.org/10.1016/j.iotcps.2023.02.004

[16] Roostaei, J., Wager, Y. Z., Shi, W., Dittrich, T., Miller, C., & Gopalakrishnan, K. (2023). IoT-based edge computing (IoTEC) for improved environmental monitoring. Sustainable Computing: Informatics and Systems, 38, 100870. https://doi.org/10.1016/j.suscom.2023.100870

[17] Kong, L., Tan, J., Huang, J., Chen, G., Wang, S., Jin, X., Zeng, P., Khan, M., & Das, S. K. (2022). Edge-computing-driven Internet of Things: A survey. ACM Computing Surveys, 55(8), Article 174. https://doi.org/10.1145/3555308

[18] Tuli, S., Mirhakimi, F., Pallewatta, S., Zawad, S., Casale, G., Javadi, B., Buyya, R., & Jennings, N. R. (2022). AI augmented edge and fog computing: Trends and challenges. Journal of Network and Computer Applications, 216, 103639.

[19] Jagatheesaperumal, S. K., Pham, Q. V., Ruby, R., Yang, Z., Xu, C., & Zhang, Z. (2022). Explainable AI over the Internet of Things (IoT): Overview, state-of-the-art and future directions. IEEE Open Journal of the Communications Society, 3, 2106–2136.

[20] Laroui, M., Nour, B., Moungla, H., Cherif, M. A., Afifi, H., & Guizani, M. (2021). Edge and fog computing for IoT: A survey on current research activities and future directions. Computer Communications, 180, 210–231. https://doi.org/10.1016/j.comcom.2021.09.003

[21] Zhang, J., & Tao, D. (2021). Empowering Things with Intelligence: A survey of the progress, challenges, and opportunities in Artificial Intelligence of Things. IEEE Internet of Things Journal.

[22] Liu, D., Yan, Z., Ding, W., & Atiquzzaman, M. (2019). A survey on secure data analytics in edge computing. IEEE Internet of Things Journal, 6(3), 4946–4967. https://doi.org/10.1109/JIOT.2019.2897619

[23] Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2019). Edge Intelligence: Paving the last mile of artificial intelligence with edge computing. Proceedings of the IEEE, 107(8), 1738–1762.

[24] Liu, F., Tang, G., Li, Y., Cai, Z., Zhang, X., & Zhou, T. (2019). A survey on edge computing systems and tools. Proceedings of the IEEE, 107(8), 1537–1562