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COMPREHENSIVE SURVEY OF AIOT APPROACHES FOR WATERLOGGING CRISIS MONITORING [19]

Prof. Dr. Samir ElMougy
Department of Computer Science, Faculty of Computers and Information,
Mansoura University, Mansoura 35516, Egypt
Tel.: +201011531792
E-mail: mougy@mans.edu.eg

Prof. Dr. Mohammed Alrahmawy
Department of Computer Science, Faculty of Computers and Information,
Mansoura University, Mansoura 35516, Egypt
Tel.: +201550191970
E-mail: Mrahmawy@mans.edu.eg

Prof. Ass. Dr. M. A. El-dosuky
Department of Computer Science, Faculty of Computers and Information,
Mansoura University, Mansoura 35516, Egypt
Tel.: +201009752991
E-mail: mouh_sal_010@mans.edu.eg

Aya ElSayed Hamed, PhD Researcher
Department of Computer Sciences, Faculty of Computers, and Informatics,
Mansoura University, Mansoura 35516, Egypt
Tel.: +201066661280
E-mail: aya.hamed@gmail.com

Abstract: *Waterlogging poses a significant threat to urban areas, affecting economies, transportation, and the well-being of citizens. Existing solutions often rely on manual reports, social media, and street cameras, falling short of handling the crisis effectively. In the face of intensifying climate change, an Early Warning System (EWS) becomes imperative for hazard detection, analysis, monitoring, forecasting, and citizen alerts. This paper explores the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) to address these challenges, a paradigm known as Artificial Intelligence of Things (AIoT). AIoT combines AI's problem-solving capabilities with IoT's data collection and connectivity. This survey encompasses a review of related works and a comparison of various AIoT-based approaches, and algorithms with highlighting their strengths and weaknesses. It also addresses challenges in AIoT for waterlogging monitoring, such as security, data integrity, and latency. Notably, we examine successful implementations worldwide, including systems in China, Taiwan, and Indonesia, showcasing AIoT's effectiveness in real-world applications. The survey concludes by underlining the growing importance of AIoT in waterlogging crisis management, emphasizing the potential for further advancements and the need for collaborative efforts to enhance urban resilience.*

Keywords: *Artificial Intelligence of Things, Crisis Management, Waterlogging Crisis, Climate Changes, AIoT, EWS.*

INTRODUCTION

With the potential climate change, Early Warning Systems (EWS) to prevent water-logging disasters become a hotspot topic for research to predict and detect the risk, alert people, and make appropriate decision-making. In 2018, a new term called AIoT that combines two of the strongest abbreviations of both technologies Artificial Intelligence (AI) and Internet of Things (IoT) became

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a hot topic. In IoT solutions, data processing and output have some limitations that can be enhanced by integrating and adding AI technologies to empower these solutions. These challenges include information security risks and safety, detecting anomalies, cost, operational efficiency and productivity, and downtime.

In AIoT, systems collect vast real-time data through interconnected sensors, strategically positioned in monitoring, interaction, and connection scenarios. This data is intelligently processed and analyzed using AI technologies, encompassing Machine Learning (ML) on terminal devices, edge domains, or cloud centers. This includes functionalities like positioning, comparison, prediction, and scheduling, all contributing to effective problem-solving and decision-making. A Simplified AIoT Layered Architecture, depicted in Fig. 1, illustrates the seamless flow of real-time data collected from connected smart devices through the edge to the AI Edge computers and IoT Gateway layer for processing, analyzing, executing, and then storing data in the Cloud Computing and Data Center layer to automated control, demonstrating the holistic approach of AIoT platforms.

Building efficient EWS of urban waterlogging events led to better revealing its evolution mechanism and has an impact significance in managing of urban waterlogging crisis (Yang, H., Wang, Y., Jaber, N., 2023). The main idea behind the paradigm of merging AI with IoT is to efficiently control physical things properties and behaviors through sensors, actuators, and communication technology and turn collected sensor data into actionable and real-time decisions while ensuring trust, privacy, and security. Building an AIoT platform can overcome some of the limitations of the current practice of IoT solutions and make full interoperability of interconnected devices possible. Also, this integration provides them with an always higher degree of smartness by enabling their adaptation and autonomous behavior while ensuring trust, privacy, and security by Considering low power techniques, and low resource techniques of IoT devices.

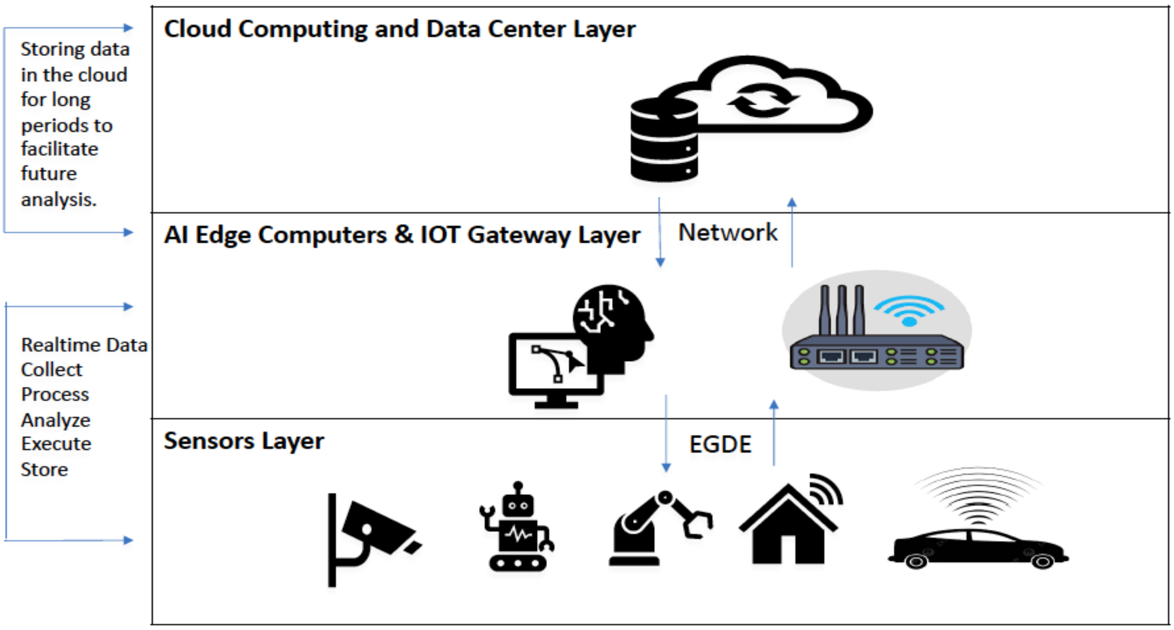

Fig. 1. Simplified AIoT Architecture

The subsequent sections of the paper extend the introductory discussion by conducting a comprehensive exploration of AIoT approaches for waterlogging crisis monitoring. The Literature Review and Related Works section provides an overview of the IoT field, highlighting challenges like security, privacy, data integrity, big data analysis, and latency. The Methodologies and Algorithms section delves into diverse AIoT systems, discussing impactful methodologies such as the integration of Random Forest, Decision Tree, and Deep Learning algorithms. This section not only emphasizes their impact but also addresses limitations, suggesting avenues for improvement. The Case Studies section offers real-world examples from China, Taiwan, and Indonesia, showcasing successful AIoT implementations in waterlogging crisis management. Notably, these practical applications are evaluated using robust metrics outlined in the dedicated evaluation metrics section. This evaluation emphasizes the effectiveness of AIoT solutions in addressing waterlogging challenges. Finally, the conclusion and future work section reflects on insights gained, setting the stage for future research directions and advancements in AIoT for waterlogging crisis monitoring.

LITERATURE REVIEW AND RELATED WORKS

IoT is promising and growing very fast as a vital branch of science and industry. It is used in most applications and through different activities of humanity. Normally, it is composed of different sensors and actuator devices such as cameras, cell phones, and vehicles. Simply, it is composed of types of things that relate to the characteristics of sending and receiving data among the other connected and/or other used infrastructure. The main challenges that face IoT are security and privacy, data integrity and big data analysis, and latency (Atzori, L., Iera, A., Morabito, G., 2010).

In (Dar, M.A., Wani, T.M., Pottoo, S.N., Mir, S.A., 2018), the authors clarified how AI as a technology can be used in combination with IoT to overcome these challenges. For example: to minimize IoT security risks, context-aware security systems and alarms for IoT devices can be implemented based on AI. AI finds ways to analyze massive amounts of data collected from the sensors as it is not possible for a human to understand these big data. Fog computing can be used to reduce latency of controlling IoT devices remotely as it processes and analyzes power close to, or within, the devices themselves.

METHODOLOGIES AND ALGORITHMS

Methodologies and algorithms play a pivotal role in the effectiveness of AIoT systems for waterlogging crisis monitoring. This section offers a more detailed explanation of the methodologies employed, shedding light on their implementation, the rationale behind their selection, and the criteria used for performance evaluation.

In the study by Boulouard et al. (Boulouard, Z., Ouaissa, M., Ouaissa, M., Siddiqui, F., Almutiq, M., Krichen, M., 2022), an AIoT-based architecture was implemented to address effective data collection, analysis, and the prevention of imminent flooding. This architecture has three levels: 1) sensors, 2) LPWAN infrastructure, and 3) a ML-based control. The authors implemented some AI algorithms such as the Random Forest (RF) algorithm that shows the best performance in all metrics, followed by, the Decision Tree (DT) and DL algorithms. The rationale for selecting these algorithms lies in their proven performance metrics, with RF exhibiting superior results. To improve this system, the authors proposed improving the sensors layer in the future by implementing an ML model inside a microcontroller that can equip each local hub.

Phratepa et al. developed an integrated predictive model using a Multiclass NN Algorithm for flood disaster prediction (Phratepa, T., Thongkhaewb, S., & Praneetpolgrang, P., 2023). The methodology involved leveraging a dataset from sensors capturing rainfall data in Thailand from 1901-2018. The algorithm's accuracy exceeded 95 %, making it a suitable choice for precise prediction. The decision to use a Multiclass NN Algorithm was rooted in its ability to handle complex patterns in the dataset, contributing to the system's robust predictive capabilities.

Liu et al. proposed applying the LSTM model by training it on the results gained from a numerical model for predicting and simulating the waterlogging process (Liu, Y., Liu, Y., Zheng, J., Chai, F., Ren, H., 2022). The numerical part was used for simulating and calculating the ponding depth of each ponding point. The results validated the proposed work, demonstrating an improvement in predicting ponding situations.

In the work by Faudzi et al. (Faudzi, A.A.M., Raslan, M.M., Alias, N.E., et al., 2023) an IoT-based real-time EWS for flood prediction utilized Long Short-Term Memory (LSTM) networks based on historical data. The rain gauge and water level sensors, strategically placed at potential flooding areas, fed data to the LSTM models. Achieving an accuracy of above 95 %, the LSTM models proved effective in predicting future rainfall and water levels. The LSTM's ability to capture long-term dependencies in sequential data made it a suitable choice for this real-time predictive application. This approach aligns with Liu et al.'s work, showcasing the effectiveness of LSTM models in improving prediction outcomes for waterlogging scenarios (Liu, Y., Liu, Y., Zheng, J., Chai, F., Ren, H., 2022).

Chen et al. (Chen, J., Li, Y., Zhang, S., 2023) constructed a flood prediction model using a combination of Convolutional Neural Network (CNN) and LSTM classifiers. Their work achieved accurate predictions and enhanced prediction times, contributing to the required emergency flood control. This approach aligns with Liu et al.'s work (Liu, Y., Liu, Y., Zheng, J., Chai, F., Ren, H., 2022), showcasing the effectiveness of LSTM models in improving prediction outcomes for waterlogging scenarios.

Pham Quang and Tallam applied ML algorithms (ANNs, SVM, and KNN) for flood disaster forecasting in Vietnam's central region (Pham Quang, M., Tallam, K., 2022). The choice of these algorithms was based on their suitability for classification tasks. ANNs demonstrated the highest performance scores, emphasizing their efficacy in predicting complex relationships within the dataset followed by SVM and KNN. The authors employed confusion matrices to evaluate accuracy, precision, and F1-score, providing a comprehensive assessment of the proposed work.

Himeur et al. discussed the need for novel environmental monitoring datasets along with unique characteristics using explainable AI and data fusion for RS image analysis, such as diverse environmental impacts and various image types from multiple sensors (Himeur, Y., Rimal, B., Tiwary, A., Amira, A., 2022). Deep Learning (DL) models, specifically DCNNs, for RS image understanding, restoration, and fusion tasks have been implemented for detecting different environmental impacts, e.g. LULC change, waterlogging, gully erosion, land salinity, and infertility. Additionally, advanced ML-based fusion techniques were proposed to improve spatial resolution and accuracy in environmental monitoring. The results showed that the acceptable classification accuracies have been achieved.

Guo et al. proposed and developed an EWS, called AutoML, using ML based on Genetic Algorithms (GAs) for some areas of Tianjin city (Guo, Y., Quan, L., Song, L., Liang, H., 2022). It also provides a comprehensive analysis of urban waterlogging through differentiating with the other ML algorithms: Categorical Boosting, eXtreme Gradient Boosting, and Back Propagation DNN, for urban waterlogging maps provided by Tianjin Meteorological Administration, were employed as the input sources. The results showed that AutoML has a good performance in forecasting waterlogging depths.

In conclusion, the methodologies and algorithms employed in these AIoT systems are diverse and impactful, each selected based on its specific strengths and suitability for the given task. The integration of these approaches contributes to the robustness of AIoT applications in waterlogging crisis management. The performance evaluation criteria include metrics such as accuracy, precision, and response time, ensuring a comprehensive assessment of their effectiveness in real-world scenarios.

EVALUATION METRICS

The assessment of Artificial Intelligence of Things (AIoT) systems necessitates the application of robust evaluation metrics to gauge their performance accurately. In this section, we delve into the criteria used to measure the effectiveness of the proposed AIoT approaches, encompassing a range of evaluation metrics.

- **Accuracy:** Reflecting the overall correctness of predictions, accuracy is calculated as the ratio of correctly predicted instances to total instances, offering a holistic performance view.
- **Precision:** his metric focuses on the accuracy of positive predictions, representing the ratio of true positive predictions to the sum of true positives and false positives. Precision is crucial for precisely identifying at-risk areas in waterlogging crisis management.

- **Recall (Sensitivity):** Assessing the system's effectiveness in capturing all positive instances, recall is calculated as the ratio of true positives to the sum of true positives and false negatives. High recall ensures potential waterlogging events are not overlooked.
- **F1-Score:** Harmonizing precision and recall, the F1-Score provides a balanced measure by calculating the harmonic mean of these metrics. It is particularly valuable in scenarios where maintaining a balance between precision and recall is essential.
- **Specificity (True Negative Rate):** Focusing on the system's ability to correctly identify non-risk areas, specificity is calculated as the ratio of true negatives to the sum of true negatives and false positives. It complements recall by addressing accuracy in discerning non-prone areas.
- **Area Under the Receiver Operating Characteristic (AUROC):** AUROC assesses the overall discriminatory ability of the AIoT system by plotting the true positive rate against the false positive rate. A higher AUROC indicates superior discriminatory power across different thresholds.
- **Confusion Matrix Analysis:** Utilizing confusion matrices allows for a granular evaluation, breaking down predictions into true positives, true negatives, false positives, and false negatives. This detailed analysis provides insights into the strengths and weaknesses of the AIoT system.

Incorporating these evaluation metrics allows for a comprehensive and nuanced assessment of AIoT systems in the context of waterlogging crisis monitoring. As the field advances, continual refinement of these metrics and the exploration of additional criteria will contribute to a more nuanced understanding of AIoT effectiveness.

CASE STUDIES

Xia et al. designed and implemented Monitoring and EWS for Beijing Urban areas Waterlogging by using sensors and wireless transmission technologies (Xia, Z.C., Zhong, X.J., Ruan, F., 2013). This system gives real-time information to perform decision-making strategies and technical support of drainage management, and releases water monitoring information to the public. It depends on classifying the alerts into 4 levels based on the water depth and waterlogging time. It consists of 3 modules: receiving water information, water monitoring, and EWS, and a warning messages service.

An urban flood control management system was developed in Chongqing – China based on IoT to monitor urban waterlogging prevention, provide operational services, conduct monitoring and early warning management, realize comprehensive supervision management, and improve the city's decision-making (Ma, Q., Yang, B., Wang, J., 2017). The solution did not use AI techniques for prediction or improving the system's performance.

Fig. 2 shows a visual sensing approach based on Deep Neural Networks (DNNs) and information and communication technology to provide an end-to-end mechanism to realize and predict waterlogging sensing and event-location mapping in the monsoon season in Taiwan (Lo, S.W., Wu, J.H., Chang, J.Y., Tseng, C.H., Lin, M.W., Lin, F.P., 2021). The system assumed locations to install the sensors instead of detecting the most suitable locations to improve the performance.

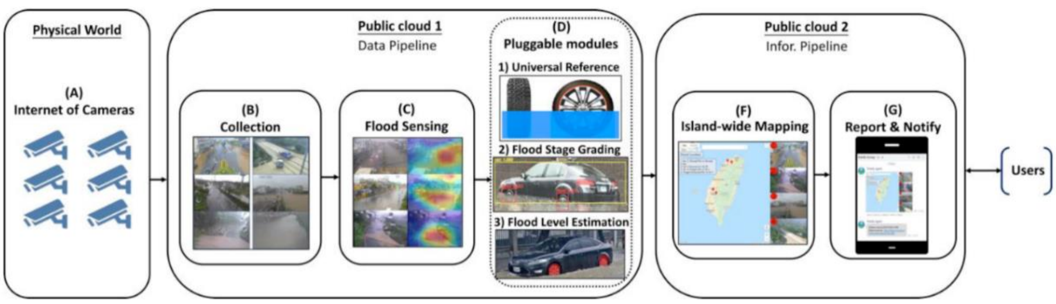

Fig. 2. Taiwan AIoT solution to predict waterlogging sensing and event-location mapping

In Indonesia, a real-time Early warning based on AIoT to monitor flash floods on flood-prone mountain slopes was proposed (Sung, W.T., Devi, I.V., Hsiao, S.J., 2022). The system design includes: 1) the integration of sensors into the microcontroller, 2) communication between the posts using LoRa and SIM900 sends data to the cloud server via the Internet, and 3) all the sensor readings for each post are displayed on the app, and alerts are sent via SMS and the app. A fuzzy method is used to calculate and analyze various environmental variables. Also, the authors proposed and developed adding more environmental parameters to provide more accurate analysis results in the future.

CONCLUSION AND FUTURE WORK

As climate change intensifies, the paper emphasizes the growing importance of Artificial Intelligence of Things (AIoT) in waterlogging crisis management through enhanced monitoring approaches. The survey reviewed and compared various AIoT-based approaches and algorithms, highlighting their strengths and weaknesses with a particular emphasis on successful global implementations in China, Taiwan, and Indonesia, demonstrating the effectiveness of AIoT in real-world applications.

However, it is essential to acknowledge the existing limitations and challenges in the current landscape. The latency associated with transmitting extensive IoT data in networks remains a concern, demanding further exploration to achieve real-time responses through high-performance AI analytics. Standard architectures for AIoT Early Warning Systems are yet to be fully established, emphasizing the need for continued research and development in this domain. Furthermore, the security of IoT systems, both in physical and technical dimensions, continues to be a primary concern. Additionally, the issues of expensive software, compatibility limitations in hardware, and the overall cost of implementing AIoT platforms underscore the importance of ongoing efforts to make these technologies more accessible and sustainable. Critical to future research is the development and refinement of algorithms for optimal sensor distribution, enhancing data collection precision and analysis efficiency.

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