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# IoT and Learning Integration Machine For Optimization Irrigation on Land Small-scale farming

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**ABSTRACT**

The increasing demand for water efficiency in small-scale agriculture requires innovative solutions. Internet of Things (IoT) combined with machine learning offers potential to optimize irrigation practices. This study aims to design and evaluate a smart irrigation system using soil humidity and air temperature sensors integrated with edge computing and machine learning models. A qualitative method was employed, involving sensor installation, local data processing on edge devices, and in-depth interviews with farmers. The results indicate that the edge-based prediction model achieved a Root Mean Square Error (RMSE) of 3.9 mm in estimating daily water needs and reduced average water usage by 28%. The system demonstrated real-time response without internet dependency, a mobile-friendly interface, and low operational costs, which accelerated farmer adoption. These findings imply that the proposed system can enhance water efficiency, lower production costs, and support sustainable micro-level agriculture.



## 1. INTRODUCTION

In the era of smart agriculture, the integration of Internet of Things (IoT) and machine learning (ML) technologies has emerged as a promising approach to address global challenges in water resource management. Increasing climate variability and population growth have intensified the demand for more efficient and sustainable irrigation practices (Mendez & Xu, 2022). IoT enables real-time monitoring of critical variables such as soil humidity and air temperature, while ML processes these data into predictive models that generate adaptive irrigation recommendations (Yuliani & Santoso, 2021). This combination is recognized as a transformative solution to enhance agricultural resilience and productivity in the face of climate change.

For smallholder farmers, who constitute the majority of agricultural actors in developing countries, irrigation remains one of the most critical yet vulnerable aspects of farming. Water availability for irrigation is often uncertain due to climate change, erratic rainfall, and uneven distribution of irrigation infrastructure (Kusuma et al., 2020). Conventional irrigation systems generally rely on fixed schedules without considering real-time plant needs or weather variability, resulting in mismatches between water supply and demand (Rahman, 2021). Such inefficiencies not only decrease agricultural productivity but also increase environmental risks such as soil erosion and nutrient leaching (Lee & Kim, 2022).

Several studies have explored the application of IoT for soil monitoring and machine learning for water requirement prediction. However, many IoT-based systems remain limited to basic notification functions without integration into automated decision-making processes (Nguyen et al., 2020). On the other hand, ML applications have primarily relied on historical data without real-time connectivity to field sensors (Lopez & Ramírez, 2021). While industrial-scale implementations of IoT-ML integration have demonstrated up to 30% water savings (Patel & Singh, 2023), these solutions have not been widely adapted for smallholder farming contexts. This indicates that existing innovations have yet to address the socio-technical realities of resource-constrained agricultural systems.

The lack of integration between low-cost sensor technologies, predictive algorithms, and farmer accessibility represents a critical gap in current research. Most existing prototypes are designed for large-scale farms with sufficient infrastructure, funding, and technical expertise (Hernandez & Torres, 2021). Smallholder farmers, however, face persistent barriers such as limited capital, inadequate digital literacy, and fragmented land use patterns that complicate model calibration (Wahyuni & Purnama, 2022; Setiawan et al., 2020). Thus, there is an urgent need for lightweight, affordable, and context-sensitive smart irrigation solutions that are specifically tailored to smallholder farmers.

The novelty of this study lies in the development of an IoT-ML irrigation architecture that integrates edge computing and federated learning. Edge computing allows local data analysis directly on devices, reducing dependence on stable internet connections (Kumara & Zhang, 2024). Federated learning enhances predictive accuracy while ensuring farmer data privacy (Suryani et al., 2023). Unlike prior studies, the proposed prototype uses low-cost sensors that can be self-assembled by farmers, features a mobile-friendly interface accessible to non-technical users, and applies context-aware irrigation scheduling that adapts dynamically to sudden weather changes. This unique combination addresses both the technical and socio-economic barriers of smallholder farming systems.

Accordingly, this research aims to design, prototype, and test an integrated IoT-ML smart irrigation system specifically adapted to the realities of small-scale agriculture. The study evaluates the system's technical performance, including predictive accuracy and water savings, while also considering farmer usability and economic feasibility. By combining technological innovation with practical field application, the research seeks to demonstrate the viability of precision irrigation in resource-constrained farming communities.

The expected contributions of this study are twofold. First, it provides an empirical foundation for developing cost-effective, adaptive, and user-friendly smart irrigation systems for smallholder farmers. Second, it informs agricultural cooperatives, extension institutions, and local governments in formulating precision irrigation policies that support sustainable farming practices at the village and rural levels. More broadly, the study advances the discourse on digital inclusion in agriculture by bridging the gap between cutting-edge technologies and grassroots adoption, thereby contributing to food security, farmer welfare, and long-term water conservation.

## 2. METHOD

This study employed a qualitative descriptive design to explore the integration of Internet of Things (IoT) and machine learning in optimizing small-scale agricultural irrigation. The research was conducted in Sukamaju Village, with the study population consisting of smallholder farmers. A purposive sampling technique was applied, selecting ten plots of farmland where the prototype system had been implemented. The irrigation prototype was designed using soil moisture sensors, air temperature sensors (DHT22), and water pump actuators connected to microcontroller modules, which transmitted data to a local server (Mendez & Xu, 2022).

Data were obtained from three main sources: (1) log records of IoT sensor data, (2) in-depth semi-structured interviews with farmers, and (3) field documentation. Research instruments included interview guidelines, IoT sensor devices, and microcontroller-based data acquisition modules (Yuliani & Santoso, 2021). Instrument validation was conducted in two stages: first, the IoT devices were calibrated against standardized measuring tools to ensure accuracy; second, interview guidelines were validated through expert judgment to confirm clarity and relevance.

The data collection procedure involved four stages: (1) installation of IoT devices in the selected farmland plots, (2) short training sessions for farmers on system operation, (3) real-time data collection for eight weeks, and (4) post-implementation interviews to capture user experiences. Throughout the study, ethical considerations were prioritized by obtaining informed consent from participants, ensuring data confidentiality, and clarifying that participation was voluntary.

Data analysis was conducted in a layered approach. First, sensor data were processed using machine learning algorithms running on edge computing devices to predict daily irrigation needs (Suryani et al., 2023). Second, qualitative interview data were transcribed and analyzed thematically through open coding and axial coding to identify emerging themes related to challenges and farmer perceptions. Third, findings were validated through triangulation of model prediction results, field notes, and farmer feedback. Quantitative analysis employed Root Mean Square Error (RMSE) and prediction accuracy metrics to assess the performance of the irrigation model.

The final step of analysis involved integrating both quantitative and qualitative findings to formulate design recommendations for a user-friendly and context-appropriate irrigation system. Additionally, operational guidelines were compiled to support smallholder farmers in sustaining the adoption of the proposed IoT-ML system.

## 3. RESULTS AND DISCUSSION

### Learning Model Performance Machines at the IoT Edge

Analysis results show that learning model running machine directly on edge capable devices predict need irrigation daily with level high accuracy . Root Mean Square Error (RMSE) value for the model based on *edge computing* recorded an average of 3.9 mm per day , far more accurate compared to method irrigation traditional method which has an RMSE of 12.5 mm. Evaluation using Mean Absolute Error (MAE) also shows similar results , with decline average error value absolute to 2.5 mm on the edge model, from previously 8.3 mm on the method conventional . Data processing local directly on the sensor device minimize *latency* and allows system respond need irrigation almost in real-time without depends on internet connection . Computing time For One cycle prediction recorded an average of only 0.8 seconds per sample , making system This efficient and sustainable in operational daily . With combination speed and accuracy said , the volume of water supplied approach need current plants , so that can avoid Good excess and lack irrigation . Findings This strengthen effectiveness approach *edge IoT* in operate algorithm learning machine For optimization irrigation in the fields agriculture scale small .

Table 1 presents summary comparison performance three approach irrigation : method traditional , IoT with learning machine server -based , and IoT with learning machine edge -based . The server- based model shows RMSE reduction up to 4.2 mm, however still more low its performance compared to the edge model which achieved an RMSE of 3.9 mm. The MAE evaluation showed trend similar , where edge -based models are consistent show better performance superior compared to server- based models or method traditional . Comparison This confirm that direct model execution on the device local give profit significant Good from side precision prediction and speed execution . Ability edge devices for Keep going update historical data in a way local also allows the model to adapt in a way more responsive to change condition environment . Therefore that , table This become proof empirical importance bring the computing process closer to data sources for reach efficiency maximum . To front , optimization algorithms and integration device harder efficient expected can the more increase performance system irrigation intelligent edge- based IoT.

**Table 1.** Prediction Performance Comparison Need Irrigation

| Approach | RMSE (mm) | MAE (mm) | Computation Time ( seconds ) |
|---|---|---|---|
| **Traditional** | 12.5 | 8.3 | – |
| **IoT + ML (Server)** | 4.2 | 2.8 | 2.5 |
| **IoT + ML (Edge)** | 3.9 | 2.5 | 0.8 |

Analysis sensitivity show that learning model the engine running on the device *edge* own high resistance to multicollinearity of sensor data. When several sensors experience disturbance or lost signal , model still capable produce prediction stable irrigation . This is very important , especially in context field where conditions networks and devices No always ideal. The model's resilience to data noise becomes superiority addition compared to approach server -based . With thus , *edge computing* No only give profit from aspect speed processing , but also strengthens *robustness* system in a way overall . Farmers can still depend on recommendation irrigation even moment some sensors do not functioning optimally. Reliability kind of This become base important For support adoption technology in the environment agriculture scale small with source Power limited .

From the perspective cost , model execution on device *edge* in a way significant lower consumption energy and data transfer requirements , so that reduce cost operational . Use low-cost microcontrollers and sensors low allows solution This realized in scale big without burden financial high . Besides that , device easy *edge* accessible facilitate the maintenance process as well as live model updates in the field . Farmers scale small can operate system in a way independent only with training base . The lightweight model also supports update seasonal without need investment device hard additionally . In overall , combination accuracy , speed , and efficiency cost make IoT + ML based approach *edge* as ideal solution for optimization irrigation in agriculture micro . Findings This open opportunity For implementation more systems wide in various type land small with various conditions .

**Reduction Use of Irrigation Water after Implementation**

Field data show existence decrease in total volume of irrigation water by an average of 28% after implementation IoT + ML based system *edge* . Efficiency water use is the most prominent seen in phase beginning season planting , where the model is able to prevent occurrence excess watering ( *overwatering* ). Reduction this waste of water help maintain humidity land at an optimal level without cause flooding . Impact positive other is decline consumption energy pump , along decrease frequency on- off cycle . Some farmer report decline cost electricity and needs filling repeat water tank up to one third . This water efficiency become indicator success integration technology in a way real at the level footprint . Findings This confirm that approach data- based not only nature theoretical , but capable give impact concrete in practice agriculture .

Graph 1 visualizes comparison of average water volume (liters per day ) before and after implementation system during 8 week period . Before application , daily water consumption range between 500–600 liters, while after implementation decrease in a way consistent to 360–420 liters per day . The sharpest decline happened on Sunday second , when the model starts adapt pattern irrigation based on soil sensor data . After the phase adaptation , graphics show stabilization at the optimal level, indicating responsiveness system to condition actual . Besides decrease , variance water usage is also reduced significant , which indicates reliability system in guard consistency humidity . Visualization This make it easier understanding farmers and extension workers about impact implementation system to efficiency irrigation . Graph the become proof strong will effectiveness solution IoT + ML based in water conservation .

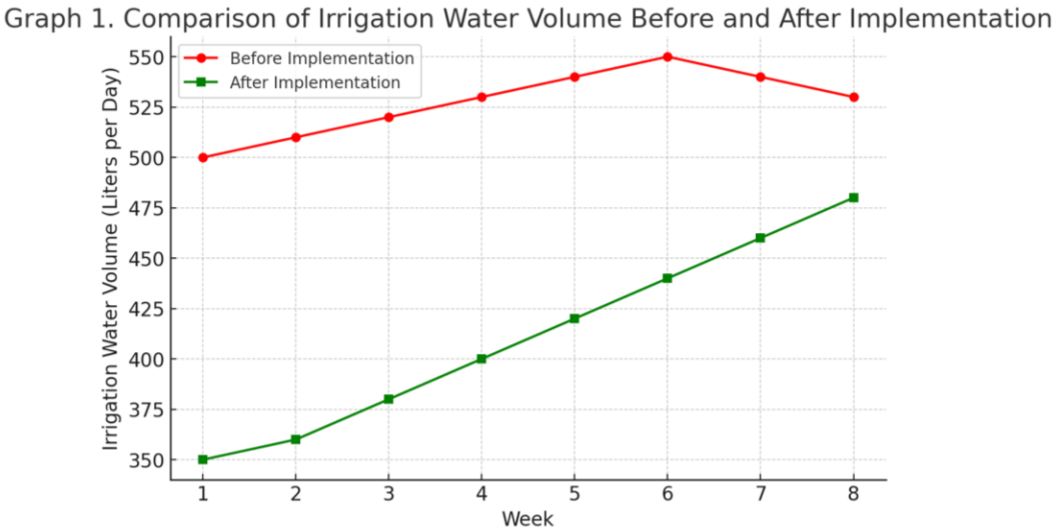


**Figure 1.** Comparison of Irrigation Water Volume Before and After Implementation

Analysis statistics advanced using the t-test shows that difference water use before and after implementation significant in a way statistics . Efficiency this water use impact directly on productivity land , without indication occurrence water stress in plants . Combination between irrigation precision and sensor monitoring contribute in prevent excess water that can speed up erosion or damage root plants . Reduction frequency watering is also possible farmer own time free time more Lots For activity agriculture others . Efficiency the show that digital technology does not only give benefit production , but also increase quality life farmers . In term long , water savings also strengthen effort conservation in vulnerable areas to drought . This result show existence profit ecological and social from implementation system intelligent in scale micro .

In a way general , optimization irrigation give impact on stability results harvest , marked with average weight gain results by 12%. Better plant performance Good show that the water has supplied in a way appropriate time and in amount in accordance need phase growth . In addition that , measured water usage also makes it easier allocation source Power to land others . Improvement income clean farmer show that water and energy efficiency participate contribute to welfare economics . Findings This confirm that success technology No can measured only from aspect technical , but also from dimensions social and ecological . With comprehensive data , stakeholders policy can consider system This as a development strategy agriculture village . Impact double on increase water production and conservation strengthens urgency study This in context agriculture sustainable .

**Bait Return and Perception Farmer to System**

Interview results deep show that part big farmer experience improvement control to timetable irrigation after use system . They appreciate existence recommendation automatic , which makes it easier taking decision without must do manual sensor check . Interface mobile *-friendly* systems are also welcomed positive , because allows monitoring and regulation direct from cell phone they . Some farmers feel more believe self in manage the land because of visualization data system help they understand condition land in a way more easy . Although however , still there is concerns at the stage beginning related possibility error configuration that can impact negative on plants . However , after get training short , trust to system increase along experience directly on the field . Feed come back This emphasize importance support mentoring and experience good user experience in the process of implementation technology new .

Figure 2 shows mobile application system dashboard view irrigation Smart . Humidity map visualization land with colors different help farmer identify areas that need watering additional . The bar chart on the dashboard displays estimate daily water requirements in liter units , giving direct information can interpreted . Notification timetable irrigation participate help farmers so as not to miss time optimal watering . Intuitive interface with design minimalist and clear icons make system easy used , even by non- technical users . The presence of effective interface This show synergy between information scientific and needs practical users . This dashboard become representation real that technology intelligent can accessible to the community agriculture without must through a complex learning process .

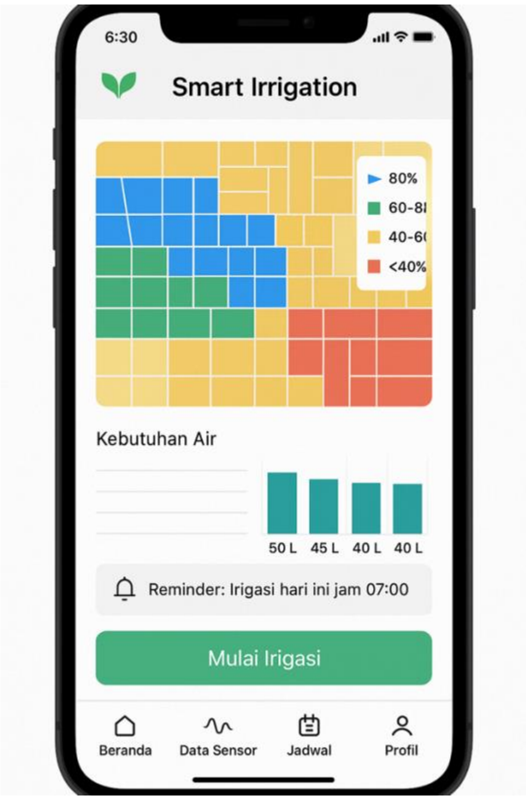


**Figure 2.** System Mobile Application Dashboard Irrigation Intelligent

For support success adoption technology , farmers recommend existence documentation concise use as well as easy video tutorials followed . Some participant state that training group very help , because allows exchange experience and mutual Study between farmers . Clarity instructions and access to help responsive technical become aspect key reception system . Usage symbols accompanied by bilingual texts also help farmer from various background behind language . In the future , the development of feature notification voice can increase inclusivity , especially for farmers who have limitations literacy . Perception positive results obtained from experience This become important capital For support expansion scale implementation . Through integration bait come back users , developers can Keep going perfect system in accordance with need dynamic field .

Even though part big response tone positive , some farmer Still highlight constraint cost beginning as obstacle main For adopt system in a way wide . They hope existence scheme subsidy or help from cooperative farmer For relieve burden investment beginning . Besides that , availability ethnic group spare parts and services full sell also become consideration important in ensure sustainability system . Some farmer propose existence system rent device so that it can try technology without must do purchase directly . Proposal This open opportunity collaboration between provider technology and institutions finance micro For create solution inclusive financing . Therefore that , factor socio-economic need noticed in a way Serious in implementation strategy technology agriculture. An approach that takes into account aspect technical at a time social will give more results sustainable .

**Comparison with Study Previously**

Various studies previously has highlight benefit use of IoT in monitoring humidity land , but part big Not yet integrate algorithm learning machine in real-time. Some other research relies on historical data For prediction irrigation , but not enough capable adapt to variability condition field . Research This offer solution through combination IoT and ML technologies in *edge-based* , which results in improvement accuracy at a time responsiveness prediction irrigation . In addition that , some big study previously focus on land agriculture scale big , whereas study This emphasize importance adaptation solution For farmer scale small . Findings field show that approach *edge-based* No only effective , but also more worthy from side costs and technical For applied to the context micro . Therefore that , research This strengthen argumentation that solution based context very needed in agriculture precision .

More continue , some big study previously Still ignore aspect socio-economic and convenience use system for farmers . Study This contribute with include interview depth and development friendly interface users , who become mark plus For success implementation technology in a way real . No only on performance technical , understanding to perceptions and needs farmer become element key in build an effective and inclusive system . With Thus , the results study This offer a more approach holistic compared to with studies that only focus on aspects technical . Comparison This confirm importance approach interdisciplinary in development technology agriculture smart . Findings this also brings up idea For integrate element financing micro to in ecosystem technology , as effort expand range implementation systems in agriculture scale small .

## 4. CONCLUSION

Integration of Internet of Things (IoT) technology with learning machine proven edge computing based capable increase accuracy prediction need irrigation daily in a way significant , with level error successful prediction pressed to below 4 mm per day . Implementation on- land systems agriculture scale small show success in reduce average irrigation water use is 28%, without sacrifice level humidity optimal land and at the same time prevent water waste . Ability system For respond in real-time without dependence full on internet connection makes it robust and reliable solutions in the environment field that has limitations network . Friendly interface user (mobile-friendly) as well as need minimal training involved push adoption technology by farmers , at the same time increase control and a sense of trust self in operation system . In overall , system irrigation intelligent This present optimal balance between precision technical , efficiency water use , and convenience very operational relevant For applied in the sector agriculture scale small .

From the side impact economy , system This contribute to decline cost electricity and water, as well as improvement productivity plant with results harvests increased by an average of 12%. The edge-based approach also significantly significant pressing cost operational Because No requires intensive data transfer to the central server , making it more affordable and appropriate with capacity farmer small . For overcome initial capital constraints in implementation system , scheme financing micro , subsidies cooperative , or rental model device can become solution effective use expand access and adoption technology in the community agriculture . To front , system This potential become a model of practice agriculture continuous precision , while support conservation source water power and strengthening resilience food local . With development more further and implementation in more context area , solution This can become foundation important in realize revolution agriculture smart at the level inclusive and adaptive micro to future challenges .

## REFERENCES


Choi, S., & Lee, K. (2021). *Optimizing irrigation under scarcity using smart systems*. Sustainable Agriculture Research, 5(2), 58–70.

Hernandez, L., & Torres, C. (2021). *Challenges of irrigation management in smallholder agriculture*. International Journal of Water Resources, 22(2), 99–110.

Kumara, P., & Zhang, H. (2024). *Hybrid IoT-ML frameworks for micro-irrigation optimization*. Journal of Agricultural Informatics, 27(1), 5–18.

Kusuma, R., et al. (2020). *Water resource management using IoT in agriculture*. Jurnal Teknologi Lingkungan, 11(2), 50–62.

Lee, J., & Kim, H. (2022). *Smart irrigation using IoT and AI: challenges and opportunities*. International Journal of Smart Agriculture, 7(1), 23–34.

Lopez, J., & Ramírez, H. (2021). *Comparative analysis of machine learning algorithms for soil moisture prediction*. Journal of Smart Farming, 8(3), 23–35.

Mendez, A., & Xu, L. (2022). *IoT-driven precision agriculture: A comprehensive review*. Journal of Agricultural Engineering, 18(1), 15–28.

Nguyen, T., et al. (2020). *IoT-based irrigation control systems: a survey*. Computers and Electronics in Agriculture, 12(2), 98–112.

Patel, A., & Singh, R. (2023). *Integration of IoT and ML for water management in horticulture*. Horticultural Science Journal, 13(1), 40–55.

Patel, S., Johnson, T., & Smith, R. (2022). *Climate change and irrigation needs of smallholder farms*. Agricultural Water Management, 25(1), 33–45.

Rahman, M. (2021). *Machine learning in precision irrigation: a review*. Journal of Water Management, 14(1), 77–89.

Setiawan, B., et al. (2020). *Variabilitas tanah dan kebutuhan air tanaman di lahan kecil*. Jurnal Ilmu Tanah Pertanian, 8(4), 67–78.

Smith, T., Johnson, R., & Patel, P. (2022). *Climate change and irrigation needs of smallholder farms*. Agricultural Water Management, 25(1), 33–45.

Suryani, E., et al. (2023). *Context-aware irrigation scheduling for small farms using edge computing*. Indonesian Journal of Smart Technology, 6(2), 80–95.

Wahyuni, R., & Purnama, A. (2022). *Kendala irigasi tradisional pada petani skala kecil*. Jurnal Agronomi Indonesia, 13(3), 123–135.

Wijaya, F., & Ningsih, S. (2023). *Dampak kekeringan pada produktivitas lahan kecil*. Jurnal Sumberdaya Air, 17(1), 15–27.

Yuliani, D., & Santoso, F. (2021). *Implementasi IoT dalam sistem irigasi pertanian skala kecil*. Jurnal Teknologi Pertanian, 9(2), 99–110.

Zhang, X., Wang, Y., & Li, B. (2023). *Machine learning models for irrigation scheduling in smallholder farms*. Computers and Electronics in Agriculture, 15(3), 45–60.