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Research Article

Integration of RF-SVM Hybrid Machine Learning Model and IoT for Water Demand Prediction and Irrigation Automation: A Systematic Literature Review and Future Research

Badie Uddin [1], Marimin [2], Sri Wahjuni [3], Budi Indra Setiawan [4]
[1, 3] *School of Data Science, Mathematics and Informatics, IPB University, Bogor, Indonesia*
[2] *Department of Agricultural Industrial Technology, IPB University, Bogor, Indonesia*
[4] *Department of Civil and Environmental Engineering, IPB University, Bogor, Indonesia*
Email: [1] badie.uddin@apps.ipb.ac.id, [2] marimin@apps.ipb.ac.id, [3] my_juni04@apps.ipb.ac.id, [4] budindra@apps.ipb.ac.id

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ABSTRACT

The management of water resources in agriculture is significantly hindered by the increasing global demand for food. Consequently, employing hybrid machine learning-based intelligent systems has emerged as a feasible approach for enhanced accuracy and efficacy in water demand forecasting. This study conducts a Systematic Literature Review (SLR) focussing on the Random Forest (RF) and Support Vector Machine (SVM) algorithms, which are commonly utilised in hybrid models, to examine recent research on the application of hybrid machine learning models in water demand prediction. Relevant materials were identified, evaluated, and analysed through the IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar databases as part of the systematic literature review procedure. The results indicate that the RF-SVM hybrid technique, when integrated with real-time data from Internet of Things (IoT) devices, enhances the accuracy of water demand prediction relative to a standalone model. Data integration, computational complexity, and restricted model interpretability are persistent challenges. The practical application is further impeded by the diversity of environmental data utilised in these studies and the limitations of extensive testing. The study identified potential areas for further research, including the development of more comprehensible and adaptive hybrid models, as well as the integration of data from several sources to enhance prediction accuracy and robustness. This study is expected to provide recommendations for practitioners and researchers on the optimal utilisation of intelligent systems in sustainable agricultural water management.

Keywords: Intelligent System, Water Demand, Hybrid Machine Learning, Random Forest, Support Vector Machine, Literature Review.

INTRODUCTION

Agriculture is a crucial sector that significantly enhances global food security and the economy of society. With population growth, the need for agricultural products escalates, rendering resource management, particularly water, crucial. Water is an essential resource in agriculture, significantly influencing crop growth and yield. The urgency of efficient water management is escalating, particularly due to the increasing worldwide water scarcity caused by climate change, population development, and agricultural expansion [1]. Effective irrigation management is essential to optimise crop yields and enhance water usage efficiency, particularly in regions facing water scarcity or alterations in rainfall patterns due to climate change [2].

Traditional irrigation management is often inefficient as it is usually based on farmer experience and manual observation, which is often inaccurate in determining crop water requirements at the right time [3]. To meet this challenge, intelligent systems for predicting water demand in agriculture are gaining ground, with great potential to optimize irrigation practices, save water use, and increase crop yields. Machine learning (ML) algorithms, especially those that utilize real-time data from Internet of Things (IoT) devices, are proving to have the ability to predict water demand with high accuracy in various agricultural contexts [4].

In recent years, there has been an increasing need for accurate and reliable prediction systems, especially in the fields of agriculture, healthcare, and the environment. Machine learning-based systems have shown great potential in processing complex data and predicting various variables precisely. Random Forest (RF) and Support Vector Machine (SVM) algorithms are two popular methods used for predictive tasks in various applications. Both have their own advantages and disadvantages, which often make them complementary in building more accurate prediction systems [5], [6].

Random Forest (RF) is an ensemble learning algorithm built on a collection of decision trees. It is known for its resistance to overfitting and its ability to work with large datasets, making it very effective in performing classification and regression[7]. The main advantage of RF is its good feature selection ability, such that the model can automatically identify the most influential variables in the dataset, improving accuracy without requiring complex pre-processing [8].

On the other hand, Support Vector Machine (SVM) is an algorithm known to be robust in handling data with non-linear patterns and works well on high-dimensional datasets. By using the hyperplane concept to distinguish classes in the data, SVM offers good performance especially in binary classification and regression problems[9]. The main strength of SVM lies in its ability to overcome linearity issues with a kernel trick, which allows the model to work on data that is not linearly separable [10].

Several studies have combined these two algorithms in a hybrid approach, utilizing RF's capability in feature selection and SVM's robustness in handling complex and non-linear patterns. This RF-SVM hybrid approach shows promising results in various fields, including disease detection, water quality prediction, and image classification, where prediction accuracy and reliability are important factors [11].

And the combination of RF and SVM is known to provide a balanced approach by utilizing RF's ability in feature selection as well as SVM's advantage in managing non-linear relationships, which results in a more reliable solution for predicting water demand. This research aims to conduct a systematic literature review to consolidate existing research on intelligent systems that combine two algorithms between RF and SVM with a hybrid machine learning model. By analyzing the current methodologies, challenges, and achievements in this domain, we hope to identify key trends and formulate new research directions in the future. Previous studies have demonstrated the potential of these models in various contexts, but significant challenges remain, including the integration of multiple data sources, real-time processing capabilities, and model interpretability [12].Addressing these challenges will be critical to advancing smart water demand prediction systems and supporting sustainable agricultural practices.

METHODOLOGY

To achieve a methodical and objective understanding of the existing literature, it is important to conduct a systematic literature review (SLR). Systematic Literature Review (SLR) is a research approach that aims to collect, select, and synthesize existing research results in a systematic and transparent manner [13]. SLR aims to reduce bias in data collection and produce a comprehensive summary of existing knowledge on a particular research topic.

In the Systematic Literature Review (SLR) method, the data collected usually comes from various reliable scientific sources. The main sources of data in SLR include journal articles, scientific conferences, technical papers, research reports, and sometimes dissertations or theses that are relevant to the topic under study. Some of the commonly used databases in SLR include [14] :

a. Scientific Journals and Conferences

The main sources for quality scientific research are journals and conference proceedings. Articles published in reputable journals and conferences have usually gone through a rigorous peer-review process, so their credibility and quality are more assured [15].

b. Academic Databases

Academic databases such as IEEE Xplore, ScienceDirect, ACM Digital Library, and Google Scholar are repositories of scientific works that are used as the main literature sources in SLR. These databases allow researchers to access scientific articles, reports, and papers relevant to the field being research [16] .

c. Dissertation and Thesis

In addition to journals and proceedings, some SLRs also consider relevant dissertations and theses to gain deeper insights or discover approaches that may not have been published in journal articles [17].

And there are two criteria that must be obtained in conducting research in order to help maintain the relevance and quality of SLR results, namely inclusion criteria and exclusion criteria. And the following criteria are expected in this study:

d. Inclusion Criteria

Includes: Publications relevant to the prediction of water demand in agricultural land, Studies that integrate IoT and Machine Learning, and Articles that present quantitative results that support the use of hybrid machine learning models for irrigation management.

e. Exclusion Criteria

Includes: Studies that are not relevant to smart irrigation or water prediction, Publications without experimental data or without quantitative validation of the model, and Studies that only use a single machine learning model without a hybrid approach.

2.1. Literature Search Strategy

Identify articles relevant to the application of intelligent systems for water demand prediction using a *hybrid machine learning* approach. The focus of the search was on Random Forest (RF) and Support Vector Machine (SVM) algorithms. In addition, to ensure a complete review, articles related to the research topic were searched in popular literature databases. The purpose of inclusion of these databases is to provide a broad view and wide coverage of the literature. The following databases were used as follows:

- Google Scholar
- Scopus
- ScienceDirect

And after conducting a literature review on these 3 databases, various journals and scientific papers were found on the topic to be discussed in this journal. And in the search conducted in the last 10 years from 2013 to 2023 we got the results as shown in Table 1.

Table I. Literature Review Results

Database	Keyword	Total paper
Google Scholar	"Intelligent system" AND "water demand prediction" AND "hybrid machine learning"	150
Scopus	"Random Forest" AND "Support Vector Machine" AND "water management"	120
ScienceDirect	"IoT" AND "machine learning" AND "agriculture water demand"	100
TOTAL		370

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2.2. Selection Paper

The article selection process in this study was conducted systematically to ensure that only relevant, quality, and fit-for-purpose literature was included in the analysis. The selection was done through several stages, based on a protocol designed according to the *Systematic Literature Review* (SLR) method. The following are the stages of selection shown in figure 1:

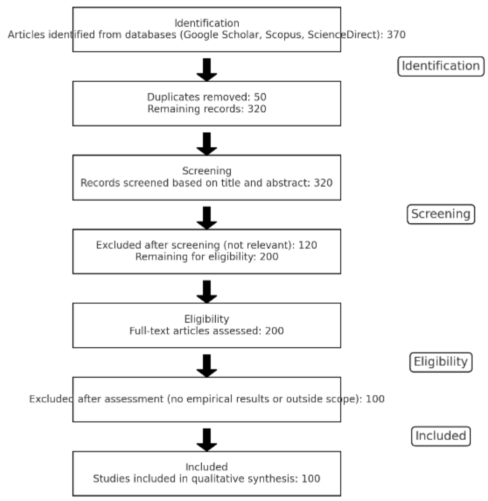

Figure 1. Stages of Literature Selection with PRISMA

One hundred relevant articles that met the inclusion criteria were identified for further evaluation. In this article, we discuss various hybrid machine learning methods, specifically the combination of Random Forest (RF) and Support Vector Machine (SVM) algorithms, and how they are used in intelligent systems to predict water demand in real-time data. The PRISMA flowchart shown in figure 1 above illustrates the selection process, showing the steps from the initial identification to the determination of the articles to be analyzed. The structured selection method ensures the quality and relevance of the literature on which the research is based [18].

ANALYSIS AND SYNTHESIS

After going through the process of selecting and evaluating articles according to the inclusion criteria, the selected literature was categorized into three main focuses. Each focus shows trends and advances in research on intelligent water demand prediction systems using hybrid machine learning, the following three main focuses are Hybrid RF-SVM Combination, Use of IoT for Real-Time Data, and Automation of Irrigation System. The division of these focus groups aims to identify trends, advantages, and contributions of each approach to smart technology-based water demand management.

3.1. Combination Hybrid RF-SVM

In the last decade, the period between 2013 to 2023, hybrid methods combining Random Forest (RF) and Support Vector Machine (SVM) algorithms have shown significant progress in a wide range of cross-disciplinary applications. The combination of these two algorithms offers a unique synergy, where RF excels in analyzing and extracting patterns from complex and large data, while SVM is renowned for its precise classification capabilities and reliability in handling non-linear data. In the context of environment, agriculture, water quality prediction, and irrigation systems, this hybrid approach is proven to be able to generate more sophisticated predictive models, not only improving prediction accuracy but also accelerating the data-driven decision-making process. This makes RF-SVM a strategic choice for researchers and practitioners facing dynamic and heterogeneous data analysis challenges in these fields. And the following is a list of selected and top journals based on the year of publication of journals about Hybrid RF-SVM Combination in various fields, as listed in Table 2.

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Table 2. Combination RF-SVM

No	Author and Year	Title of Article / Journal	Specific Focus	Model Used
1	(Liu et al. 2013) [19]	Comparison of random forest, support vector machine and back propagation neural network for electronic tongue data classification	Environment	RF-SVM
2	(Wang et al. 2015) [20]	Flood hazard risk assessment model based on random forest	Environment	RF-SVM
3	(Pour et al. 2016) [21]	A Hybrid Model for Statistical Downscaling of Daily Rainfall	Water Quality Prediction	RF-SVM
4	(Zeng et al. 2017) [22]	Comparison of models for predicting the changes in phytoplankton community composition in the receiving water system of an inter-basin water transfer project	Water Quality Prediction	RF-SVM
5	(dos Reis et al. 2018) [23]	Spatial prediction of basal area and volume in Eucalyptus stands using Landsat TM data: an assessment of prediction methods	Agriculture	RF-SVM
6	(Jamali. 2019) [24]	a fit-for-purpose algorithm for environmental monitoring based on maximum likelihood, support vector machine and random forest	Environment	RF-SVM
7	(Bui et al. 2019) [25]	A hybrid computational intelligence approach to groundwater spring potential mapping	Water Quality Prediction	RF-SVM
8	(Al-Mukhtar. 2019) [26]	Random forest, support vector machine, and neural networks to modelling suspended sediment in Tigris River-Baghdad	Environment	RF-SVM
9	(Bondre dan Mahagaonkar. 2019) [27]	Prediction of Crop Yield and Fertilizer Recommendation Using Machine Learning Algorithms	Agriculture	RF-SVM
10	(Masih. 2019) [28]	Machine learning algorithms in air quality modeling	Environment	RF-SVM
11	(Sameen et al. 2019) [29]	Self-Learning Random Forests Model for Mapping Groundwater Yield in Data-Scarce Areas	Agriculture	RF-SVM
12	(Tehrany et al. 2019) [30]	A novel ensemble modeling approach for the spatial prediction of tropical forest fire susceptibility using LogitBoost machine learning classifier and multi-source geospatial data	Agriculture	RF-SVM
13	(Lei et al. 2019) [31]	A comparison of random forest and support vector machine approaches to predict coal spontaneous combustion in gob	Agriculture	RF-SVM
14	(Rustam et al. 2019) [32]	Random-Forest (RF) and Support Vector Machine (SVM) Implementation for Analysis of Gene Expression Data in Chronic Kidney Disease (CKD)	Agriculture	RF-SVM
15	(Wang et al. 2019) [33]	Land-cover classification of coastal wetlands using the RF algorithm for Worldview-2 and Landsat 8 images	Environment	RF-SVM
16	(Singh dan Kumar. 2019) [34]	Hybrid Prediction Models for Rainfall Forecasting	Agriculture	RF-SVM
17	(Hassan et al. 2020) [35]	Urbanization change analysis based on SVM and RF machine learning algorithms	Environment	RF-SVM
18	(Hamrani et al. 2020) [36]	Machine learning for predicting greenhouse gas emissions from agricultural soils	Environment	RF-SVM

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19	(Phiri et al. 2020) [37]	Sentinel-2 Data for Land Cover/Use Mapping: A Review	Water Quality Prediction	RF-SVM
20	(Pham et al. 2020) [38]	Head-cut gully erosion susceptibility modelling based on ensemble Random Forest with oblique decision trees in Fareghan watershed, Iran	Water Quality Prediction	RF-SVM
21	(S. Liu et al. 2020) [39]	An Ensemble Modeling Framework for Distinguishing Nitrogen, Phosphorous and Potassium Deficiencies in Winter Oilseed Rape (Brassica napus L.) Using Hyperspectral Data	Agriculture	RF-SVM
22	(Prasad et al. 2020) [40]	Application of machine learning techniques in groundwater potential mapping along the west coast of India	Water Quality Prediction	RF-SVM
23	(Sumdang. 2020) [41]	Prediction of arsenic contamination in Rayong groundwater basin using machine learning based approaches	Water Quality Prediction	RF-SVM
24	(Nafsin dan Li. 2022) [42]	Prediction of 5 - day biochemical oxygen demand in the Buriganga River of Bangladesh using novel hybrid machine learning algorithms	Water Quality Prediction	RF-SVM
25	(Sahin. 2023) [43]	Implementation of free and open-source semi-automatic feature engineering tool in landslide susceptibility mapping using the machine-learning algorithms RF, SVM, and XGBoost	Environment	RF-SVM
26	(Singha et al. 2024) [44]	Prediction of urban surface water quality scenarios using hybrid stacking ensembles machine learning model in Howrah Municipal Corporation, West Bengal	Water Quality Prediction	RF-SVM
27	(Kumari et al. 2024) [45]	Combining predictive models: Hybrid approaches in crop recommendation systems	Agriculture	RF-SVM
28	(Duan et al. 2024) [46]	Enhancing soil moisture retrieval in semi-arid regions using machine learning algorithms and remote sensing data	Agriculture	RF-SVM
29	(Chen et al. 2025) [47]	Soil water content prediction across seasons using random forest based on precipitation-related data	Agriculture	RF-SVM
30	(Daviran et al. 2025) [48]	Optimized AI-MPM: Application of PSO for tuning the hyperparameters of SVM and RF algorithms	Environment	RF-SVM

An analysis of 30 scientific journals discussing the application of the Hybrid RF-SVM method combination over the period 2013-2025 revealed that this approach has been widely applied in various fields. Most of the research focused on the agricultural sector, accounting for 39% of the total studies, demonstrating the urgency and relevance of this technology in supporting food security, irrigation efficiency, as well as precision management of agricultural resources. Furthermore, 32% of the studies were directed at environmental issues, highlighting the contribution of RF-SVM in monitoring air quality, waste management, and ecosystem preservation. Meanwhile, another 29% focused on water quality prediction, illustrating the great potential of this method to improve water resources management, including early detection of pollution and optimization of clean water distribution. The dominance of applications in the agricultural sector, along with significant contributions in the environmental and water quality fields, reflects the flexibility and effectiveness of RF-SVM in supporting ecological sustainability and better natural resource management.

3.2. Use of IoT for Real-Time Data

The application of Internet of Things (IoT) technology for real-time data collection has seen rapid development in recent years, especially in sectors such as the environment, agriculture, water quality prediction, and irrigation. IoT enables the integration of internet-connected sensors and devices to directly measure various environmental

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parameters, such as temperature, humidity, water quality, and rainfall. The advantage of this technology lies in its ability to provide continuous data, which not only improves operational efficiency but also accelerates the data-driven decision-making process. In agriculture, for example, IoT is used to precisely monitor the water needs of crops, thereby reducing resource wastage. Meanwhile, in the environmental sector, this technology helps detect changes in air or water quality in real-time, enabling quick mitigation actions against potential pollution or ecosystem changes [49]. These developments show that IoT is becoming one of the key technologies in supporting sustainability and more effective resource management in various fields. The following are the selected journals sorted by year of publication and referring to IoT technology as shown in table 3 below.

Table 3 Use of IoT for Real-Time Data

No	Author and Year	Title of Article/Journal	Specific Focus	Model Used
1	(Shah dan Mishra. 2016) [50]	IoT enabled environmental monitoring system for smart cities	Environment	IoT Sensor
2	(Addabbo et al. 2018) [51]	An IoT Framework for the Pervasive Monitoring of Chemical Emissions in Industrial Plants	Agriculture	Temperature and Humidity Sensor
3	(Alam et al. 2018) [52]	Design and Development of a Low-Cost IoT based Environmental Pollution Monitoring System	Water Quality Prediction	Water Quality Sensor
4	(Chowdury et al. 2019) [53]	IoT Based Real-time River Water Quality Monitoring System	Agriculture	Temperature and Humidity Sensor
5	(Premalatha 2019) [54]	Automatic Smart Irrigation System Using IOT	Environment	Humidity and Temperature Sensor
6	(Lakshmikantha et al. 2021) [55]	IoT based smart water quality monitoring system	Water Quality Prediction	Water Quality Sensor
7	(Islam Khan et al. 2021) [56]	IoT-based System for Real-time Water Pollution Monitoring of Rivers	Water Quality Prediction	Water Quality Sensor
8	(Tephila et al. 2022) [57]	Automated Smart Irrigation System using IoT with Sensor Parameter	Environment	Temperature and Humidity Sensor
9	(Malleswari dan Mohana. 2022) [58]	Air pollution monitoring system using IoT devices: Review	Agriculture	Temperature and Humality Sensor
10	(Garrido-Momparler dan Peris. 2022) [59]	Smart sensors in environmental/water quality monitoring using IoT and cloud services	Irrigation	Humidity and Temperature Sensor
11	(Sharma et al. 2022) [60]	IoT-Enabled IEEE 802.15.4 WSN Monitoring Infrastructure-Driven Fuzzy-Logic-Based Crop Pest Prediction	Environment	Gas Sensor
12	(Laha et al. 2023) [61]	An IOT-Based Soil Moisture Management System for Precision Agriculture: Real-Time Monitoring and Automated Irrigation Control	Environment	Sound Sensor
13	(Govindasamy et al. 2023) [62]	IoT Product on Smart Water Quality Monitoring System (Iot Wq-Kit) for Puducherry Union Territory	Environment	Temperature and Humidity Sensor

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14	(Chaudhary et al. 2023) [63]	Design and study of smart irrigation system using photovoltaic cells based smart IOT system and weather prediction system for energy and water conservation in India	Agriculture	Humidity and Temperature Sensor
15	(Barmola et al. 2023) [64]	Intelligent Bioinformatics System Architecture for Water Borne Diseases Diagnosis and Monitoring	Water Quality Prediction	Water Quality Sensor
16	(Rahmawati et al. 2023) [65]	Design of a Real Time Cow Smart Collar Health and Position Monitoring System	Irrigation	Humidity and Temperature Sensors
17	(Chang et al. 2023) [66]	Machine Learning Approach to IoT- Based Water Quality Monitoring	Irrigation	Humidity and Temperature Sensor
18	(Wu et al. 2023) [67]	Internet-of-Things-Based Multiple-Sensor Monitoring System for Soil Information Diagnosis Using a Smartphone	Environment	Gas Sensor
19	(Pandey et al. 2024) [68]	CHMP-CNN: To Implement the IoT Based Crops Health Monitoring and Prediction Using Deep Learning	Agriculture	Soil Nutrient Sensor
20	(Blinova et al. 2024) [69]	Performance Evaluation of IoT Sensors in Urban Air Quality Monitoring: Insights from the IoT Sensor Performance Test	Water Quality Prediction	Water Quality Sensor
21	(Sayyad et al. 2024) [70]	IoT based soil monitoring for precision agriculture	Water Quality Prediction	Water Quality Sensor
22	(Forhad et al. 2024) [71]	IoT based real-time water quality monitoring system in water treatment plants (WTPs)	Irrigation	Humidity and Temperature Sensor
23	(Al Jaman Chaudhuy et al. 2024) [72]	IoT Based Surface Vehicle System for Water Quality Analysis and Surveying	Agriculture	Optical and Temperature Sensors
24	(Basavaraju et al. 2024) [73]	Design and Implementation of Crop Yield Prediction and Fertilizer Utilization Using IoT and Machine Learning in Smart Agriculture Systems	Water Quality Prediction	Water Quality Sensors
25	(Vishwanath et al. 2024) [74]	IoT-Based Smart Irrigation System for Sustainable Sugarcane Cultivation: Enhancing Resource Management and Optimizing Crop Yield	Irrigation	Humidity and Temperature Sensor
26	(A et al. 2024) [75]	AI Controlled Smart IoT Based Greenhouse Monitoring System	Environment	Gas Sensor
27	(G et al. 2024) [76]	Smart Aquarium Monitoring System for Optimal Aquatic Life Management Using IoT	Environment	Temperature and Humidity Sensor
28	(C et al. 2024) [77]	Intelligent Water Management System Utilizing AI for Precision Agriculture	Agriculture	Moisture and Nutrient Sensor
29	(Haq et al. 2024) [78]	Tech-Driven Forest Conservation: Combating Deforestation With Internet of Things, Artificial Intelligence, and Remote Sensing	Agriculture	Moisture and Nutrient Sensor

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30	(Sunil et al. 2024) [79]	Integration of Convolutional Neural Networks for Real-Time Monitoring of Soil Health in Precision Agriculture	Agriculture	Moisture and Nutrient Sensor
31	(Zamora-Sanchez et al. 2024) [80]	Modular Real-Time Monitoring System Architecture for Materials and Technologies to Improve Urban Heat-Island Effect and Water Runoff in HE MULTICLIMACT	Water Quality Prediction	Water Quality Sensor
32	(Sreelatha et al. 2024) [81]	Smart Agriculture: IoT-Driven Soil Monitoring and Fertilizer Recommendation with CNN and Bidirectional GRU Models	Water Quality Prediction	Water Quality Sensor
33	(Morchid et al. 2025) [82]	IoT-enabled smart agriculture for improving water management: A smart irrigation control using embedded systems and Server-Sent Events	Agriculture	Moisture Sensor
34	(Shahab et al. 2025) [83]	IoT-driven smart agricultural technology for real-time soil and crop optimization	Irrigation	Humidity and Temperature Sensor
35	(Zhang et al. 2025) [84]	Synchronous monitoring agricultural water qualities and greenhouse gas emissions based on low-cost Internet of Things and intelligent algorithms	Environment	Gas Sensor

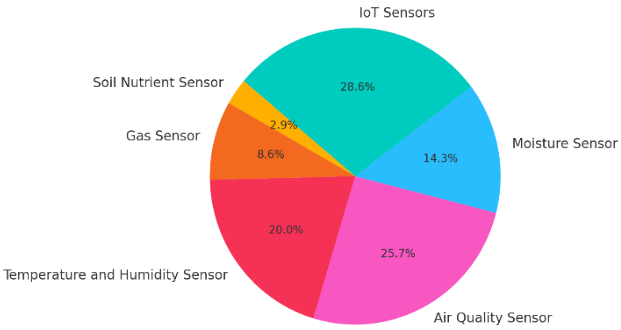

Figure 2. Sensors used in IOT Percentage Diagram

The diagram above illustrates the distribution of models used in Internet of Things (IoT) related research for real-time data collection, based on an analysis of 35 identified journals. The results show that the majority of studies utilize general IoT Sensors, which account for 29% of the overall studies, followed by Water Quality Sensors with a contribution of 26%, and Temperature and Humidity Sensors at 20%. In addition, there was use of other sensors such as Soil Moisture Sensors, Gas Sensors, and Soil Nutrient Sensors, albeit in smaller proportions. This variation reflects the flexibility of IoT technology in meeting the specific needs of different sectors.

This IoT-based approach provides an effective solution for real-time monitoring in applications ranging from precision agriculture to environmental resource management. By providing continuous and accurate data, this technology contributes to improved operational efficiency, data-driven decision-making, and supports system sustainability in various fields. The diversity of sensors used also emphasizes the role of IoT as a technology that is adaptive to complex monitoring challenges.

3.3. Automation of Irrigation System

The automation of irrigation systems has emerged as a primary area of research across multiple disciplines, including environmental science, agriculture, water quality forecasting, and irrigation management. The progression of technology has enabled the use of the Internet of Things (IoT) , artificial intelligence (AI) , and machine learning to

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develop intelligent irrigation systems that can monitor diverse environmental data in real-time. These systems can autonomously regulate the water application volume in accordance with the precise requirements of the crop, utilising data such as soil moisture, temperature, and meteorological variables. This method enhances water use efficiency, a crucial measure in the face of global water constraint, while simultaneously boosting yields by providing crops with the ideal water quantity. This technology-driven irrigation automation promotes environmental sustainability by decreasing water waste, limiting carbon emissions, and mitigating adverse effects on ecosystems. The integration of technical innovation and sustainable practices renders irrigation system automation a pertinent response to forthcoming issues in agriculture and natural resource management. The following are the selected journals sorted by year of publication and referring to Irrigation System Automation as shown in table 4 below.

Table 4. Automation of Irrigation System

No	Author and Year	Title of Article/Journal	Specific Focus	Model Used
1	(Vellidis et al. 2008) [85]	A real-time wireless smart sensor array for scheduling irrigation	Environment	Real-Time Feedback
2	(Nesa Sudha et al. 2011) [86]	Energy efficient data transmission in automatic irrigation system using wireless sensor networks	Agriculture	Embedded Systems
3	(Purnima dan Reddy. 2012) [87]	Design of Remote Monitoring and Control System with Automatic Irrigation System using GSM-Bluetooth	Environment	Solar Power
4	(Dukes. 2012) [88]	Water conservation potential of landscape irrigation smart controllers	Irrigation	IoT
5	(Wei et al. 2013) [89]	Design of real time soil moisture monitoring and precision irrigation systems	Irrigation	WSN
6	(Gutierrez et al. 2014) [90]	Automated irrigation system using a wireless sensor network and GPRS module	Agriculture	GSM Technology
7	(Henderson et al. 2018) [91]	Soil moisture sensor-based systems are suitable for monitoring and controlling irrigation of greenhouse crops	Environment	Cloud Computing
8	(Lavagno dan Passerone. 2018) [92]	Design of Embedded Systems	Agriculture	Smart Controllers
9	(Ibrahim et al. 2018) [93]	Smart irrigation system using a fuzzy logic method	Irrigation	Fuzzy Logic
10	(Singh & Kumar. 2018)	Automated Irrigation in Urban Landscaping	Irrigation	Urban Landscaping
11	(Singh & Sharma. 2018)	Machine Learning Approaches in Irrigation Automation	Irrigation	Machine Learning
12	(Chang dan Lin 2018) [94]	Smart agricultural machine with a computer vision-based weeding and variable-rate irrigation scheme	Environment	Predictive Analytics
13	(Waleed et al. 2019) [95]	Solar (PV) Water Irrigation System with Wireless Control	Agriculture	Precision Agriculture
14	(Li & Wang, 2019)	AI-Based Decision Support for Irrigation	Agriculture	AI
15	(Li & Zhang. 2019)	Real-Time Soil Moisture Monitoring for Irrigation Control	Agriculture	IoT
16	(Patel. et al. 2019) [96]	Sensor and Cloud Based Smart Irrigation System With Arduino: a Technical Review	Environment	Energy Efficiency

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No	Author and Year	Title of Article/Journal	Specific Focus	Model Used
17	(García et al. 2020) [97]	IoT-based smart irrigation systems: An overview on the recent trends on sensors and iot systems for irrigation in precision agriculture	Agriculture	IoT
18	(C. Liu et al. 2020) [98]	Pattern identification and analysis for the traditional village using low altitude UAV-borne remote sensing: multifeatured geospatial data to support rural landscape investigation, documentation and management	Irrigation	Blockchain
19	(Blasi et al. 2021) [99]	Machine Learning Approach for an Automatic Irrigation System in Southern Jorsdan Valley	Irrigation	Sensor Fusion
20	(Badrun dan Manaf. 2021) [100]	The Development of Smart Irrigation System with IoT, Cloud, and Big Data	Environment	Sustainability
21	(Sami et al. 2022) [101]	A Deep Learning-Based Sensor Modeling for Smart Irrigation System	Agriculture	AI
22	(Premkumar dan Sigappi. 2022) [102]	IoT-enabled edge computing model for smart irrigation system	Agriculture	IoT
23	(Lee. 2022) [103]	Evaluación del Sistema de Riego Automático para el Cultivo de Arroz y Manejo Sostenible del Agua para la Agricultura	Agriculture	Machine Vision
24	(Chen & Liu. 2022	Edge Computing in Smart Irrigation Systems	Agriculture	Edge Computing
25	(Bwambale et al. 2023) [104]	Data-driven model predictive control for precision irrigation management	Agriculture	Remote Sensing
26	(Zhang et al. 2023) [105]	Sustainable Food Processing, a section of the journal Frontiers in Sustainable Food Systems Artificial intelligence-based decision support systems in smart agriculture: Bibliometric analysis for operational insights and future directions	Agriculture	Deep Learning
27	(Zhang et al. 2023) [106]	Integration of IoT and AI in Irrigation Systems	Environment	IoT & AI
28	(Wei et al. 2024) [107]	Irrigation with Artificial Intelligence: Problems, Premises, Promises	Agriculture	Sensor Networks
29	(Morchid et al. 2024) [3]	High-technology agriculture system to enhance food security: A concept of smart irrigation system using Internet of Things and cloud computing	Irrigation	Cloud Computing
30	(Sreelatha Reddy et al. 2024) [108]	IoT and Cloud Based Sustainable Smart Irrigation System	Agriculture	IoT & Big Data
31	(Benhmad et al. 2024) [109]	Design and Implementation of an Integrated IoT and Artificial Intelligence System for Smart Irrigation Management	Environment	Weather Forecasting
32	(Stefanov et al. 2024) [110]	Mobile Application for Managing an Automated Irrigation System	Environment	Wireless Control
33	(Yauri et al. 2024) [111]	Sprinkler Irrigation Automation System to Reduce the Frost Impact Using Machine Learning 811 Original Scientific Paper	Irrigation	Cloud Computing

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Research Article

No	Author and Year	Title of Article/Journal	Specific Focus	Model Used
34	(Wahyudi et al. 2025) [112]	Implementasi Sistem Irigasi Otomatis Berbasis IoT untuk Pertanian Greenhouse	Irrigation	Mobile Applications

Author and YearTitle of Article/JournalSpecific FocusModel Used (Vellidis et al. 2008) A real-time wireless smart sensor array for scheduling irrigationEnvironmentReal-Time Feedback (Nesa Sudha et al. 2011) Energy efficient data transmission in automatic irrigation system using wireless sensor networksAgricultureEmbedded Systems (Purnima dan Reddy. 2012) Design of Remote Monitoring and Control System with Automatic Irrigation System using GSM-BluetoothEnvironmentSolar Power (Dukes. 2012) Water conservation potential of landscape irrigation smart controllersIrrigationIoT (Wei et al. 2013) Design of real time soil moisture monitoring and precision irrigation systemsIrrigationWSN (Gutierrez et al. 2014) Automated irrigation system using a wireless sensor network and GPRS moduleAgricultureGSM Technology (Henderson et al. 2018) Soil moisture sensor-based systems are suitable for monitoring and controlling irrigation of greenhouse cropsEnvironmentCloud Computing (Lavagno dan Passerone. 2018) Design of Embedded SystemsAgricultureSmart Controllers (Ibrahim et al. 2018) Smart irrigation system using a fuzzy logic methodIrrigationFuzzy Logic (Singh & Kumar. 2018) Automated Irrigation in Urban LandscapingIrrigationUrban Landscaping (Singh & Sharma. 2018) Machine Learning Approaches in Irrigation AutomationIrrigationMachine Learning (Chang dan Lin 2018) Smart agricultural machine with a computer vision-based weeding and variable-rate irrigation schemeEnvironmentPredictive Analytics (Waleed et al. 2019) Solar (PV) Water Irrigation System with Wireless ControlAgriculturePrecision Agriculture (Li & Wang, 2019) AI-Based Decision Support for IrrigationAgricultureAI (Li & Zhang. 2019) Real-Time Soil Moisture Monitoring for Irrigation ControlAgricultureIoT (Patel. et al. 2019) Sensor and Cloud Based Smart Irrigation System With Arduino: a Technical ReviewEnvironmentEnergy Efficiency (García et al. 2020) IoT-based smart irrigation systems: An overview on the recent trends on sensors and iot systems for irrigation in precision agricultureAgricultureIoT (C. Liu et al. 2020) Pattern identification and analysis for the traditional village using low altitude UAV-borne remote sensing: multifeatured geospatial data to support rural landscape investigation, documentation and managementIrrigationBlockchain (Blasi et al. 2021) Machine Learning Approach for an Automatic Irrigation System in Southern Jorsdan ValleyIrrigationSensor Fusion (Badrun dan Manaf. 2021) The Development of Smart Irrigation System with IoT, Cloud, and Big DataEnvironmentSustainability (Sami et al. 2022) A Deep Learning-Based Sensor Modeling for Smart Irrigation SystemAgricultureAI (Premkumar dan Sigappi. 2022) IoT-enabled edge computing model for smart irrigation systemAgricultureIoT (Lee. 2022) Evaluación del Sistema de Riego Automático para el Cultivo de Arroz y Manejo Sostenible del Agua para la AgriculturaAgricultureMachine Vision (Chen & Liu. 2022) Edge Computing in Smart Irrigation SystemsAgricultureEdge Computing (Bwambale et al. 2023) Data-driven model predictive control for precision irrigation managementAgricultureRemote Sensing (Zhang et al. 2023) Sustainable Food Processing, a section of the journal Frontiers in Sustainable Food Systems Artificial intelligence-based decision support systems in smart agriculture: Bibliometric analysis for operational insights and future directionsAgricultureDeep Learning (Zhang et al. 2023) Integration of IoT and AI in Irrigation SystemsEnvironmentIoT & AI (Wei et al. 2024) Irrigation with Artificial Intelligence: Problems, Premises, PromisesAgricultureSensor Networks (Morchid et al. 2024) High-technology agriculture system to enhance food security: A concept of smart irrigation system using Internet of Things and cloud computingIrrigationCloud Computing (Sreelatha Reddy et al. 2024) IoT and Cloud Based Sustainable Smart Irrigation SystemAgricultureIoT & Big Data (Benhmad et al. 2024) Design and Implementation of an Integrated IoT and Artificial Intelligence System for Smart Irrigation ManagementEnvironmentWeather Forecasting (Stefanov et al. 2024) Mobile Application for Managing an Automated Irrigation SystemEnvironmentWireless Control (Yauri et al. 2024) Sprinkler Irrigation Automation System to Reduce the Frost Impact Using Machine Learning 811 Original Scientific PaperIrrigationCloud Computing (Wahyudi et al. 2025) Implementasi Sistem Irigasi Otomatis Berbasis IoT untuk Pertanian GreenhouseIrrigationMobile Applications

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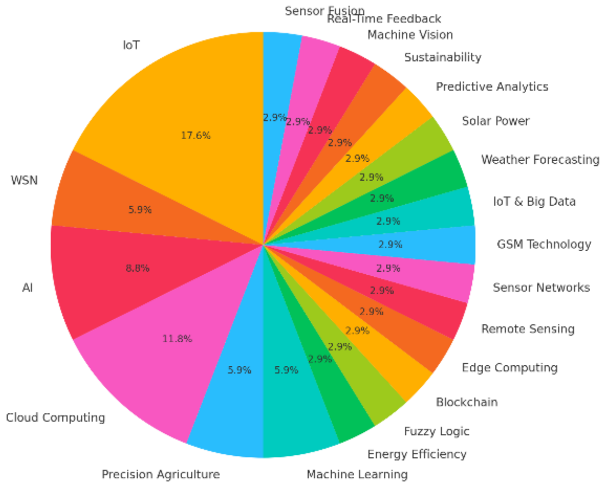

Figure 3. Model Used in Automation of Irrigation System

The data in figure 3 illustrates the various models used in research on irrigation system automation, derived from an analysis of 34 identified journals. The Internet of Things (IoT) holds a significant share of 18%, underscoring the critical role of this technology in facilitating real-time data acquisition and remote management of irrigation systems. Moreover, Cloud Computing accounted for 12%, highlighting its significance in facilitating extensive data processing and storage for subsequent analysis. Artificial Intelligence (AI), utilised in 9% of the research, shown its capacity to enhance decision-making informed by environmental data and agricultural requirements. Moreover, there were contributions from various other technologies, including Wireless Sensor Networks (WSN), Precision Agriculture, and Machine Learning, albeit in lesser numbers. This variety of methodologies demonstrates the researchers' endeavours to employ many contemporary technology to provide more efficient, adaptive, and sustainable irrigation methods. The integration of these technologies in irrigation systems seeks to enhance water use efficiency while promoting environmental sustainability and global food security.

RESULTS AND DISCUSSION

4.1. Research GAP

A systematic examination of the literature addressing the hybrid integration of RF-SVM, the application of IoT for real-time data, and the automation of irrigation systems uncovered several notable research deficiencies. These domains have prospects for further advancement, particularly in the utilisation of modern technologies to enhance the efficiency and precision of irrigation prediction and management systems. A primary finding is the insufficient in-depth research on the use of RF-SVM in hybrid machine learning (ML) -based water demand prediction, which incorporates real-time data, system optimisation, and device reliability assessment in practical scenarios.

The integration of RF-SVM has demonstrated efficacy in predicting water quality and irrigation demand, as evidenced by [49]. However, most of these studies are still limited to the use of static or historical data, which do not reflect real-time environmental changes. This gap underscores the need for the adoption of models in the context of real-time prediction, which are able to leverage IoT data to handle dynamic and complex environmental conditions. The performance of RF-SVM in hybrid ML is highly dependent on computing capacity, which is often a constraint in deployment on IoT devices with limited power and memory [113]. Future research is needed to develop a lighter and more efficient model that can be applied widely, especially in fields with limited technological infrastructure.

IoT has developed into a key technology in real-time data collection, including soil moisture, temperature, and water quality [114]. Although the potential for integration between IoT and RF-SVM is enormous, research connecting the two to create a more accurate and efficient prediction system is still very limited. In fact, this integration can provide innovative solutions for data-based water management systems. Automated irrigation systems based on IoT and AI have been widely developed, as shown in the study. However, only a few studies utilize RF-SVM as a predictive model

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to support automated decision-making in irrigation systems. In fact, this technology can significantly improve water use efficiency, especially in areas with limited resources, while optimizing crop yields. Most studies tend to focus only on model accuracy, without considering aspects of system reliability in real-world scenarios, such as sudden weather changes, IoT device failures, or network disruptions. Evaluation of system risk and reliability is essential to ensure that RF-SVM applications can survive unexpected situations and provide consistent results. The following is the percentage of research gaps in the Systematic Literature Review (SLR) based approach, with several techniques for quantifying and qualifying research gaps. And the technique used to calculate the percentage is done manually using Ms Excel. By creating a table containing columns such as in tables II, III and IV, after we use the COUNTIF () function or Pivot Table to calculate the frequency of each type of research gap. after getting the results we immediately visualize them in the form of a pie chart using tools in Ms Excel. and here are the results as in Figure 4 below.

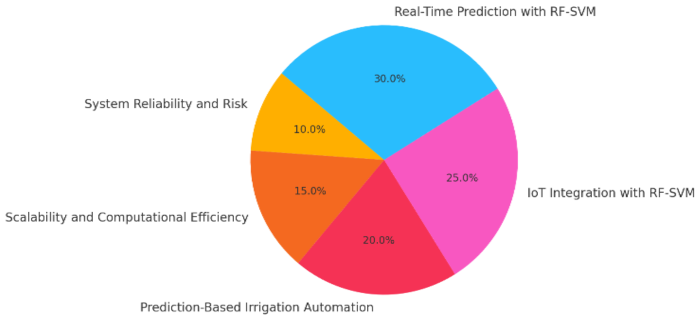

Figure 4. GAP Research

The examination of the research gap distribution indicates that the most significant gap is in real-time prediction utilising RF-SVM, accounting for 30%. This underscores the pressing necessity to include the RF-SVM model with real-time data to enhance the precision and responsiveness of the water demand forecasting system. Furthermore, the integration of IoT with RF-SVM is the secondary priority (25%), underscoring the significance of collaboration between IoT devices and hybrid machine learning models for enhanced efficiency and real-time data acquisition. Prediction-based irrigation automation utilising RF-SVM constitutes a substantial segment (20%), demonstrating considerable potential to enhance irrigation efficiency via a system that is more responsive to field requirements. Deficiencies in scalability and computational efficiency (15%) and system reliability and risk (10%) underscore the necessity for model optimisation and reliability assessment under variable environmental conditions. Subsequent research is anticipated to tackle these difficulties by creating more resilient, efficient, and dependable technologies.

4.2. Research Future

Given the acknowledged research deficiencies, many research avenues can be pursued to advance the creation of intelligent systems utilizing RF-SVM and IoT in the domain of agriculture and water resources management. The following are matters covering RF-SVM and IoT in the domain of agriculture and water resources management, including Real-Time Integration of IoT with RF-SVM, Hybrid Machine Learning (ML) -based Irrigation Automation Development, RF-SVM Optimization for IoT Devices, and System Risk and Reliability Assessment.

The research may concentrate on creating a real-time prediction model that combines the RF-SVM algorithm with IoT data to assess water requirements. This method enables the system to leverage direct environmental data, including soil moisture, precipitation, and temperature, hence facilitating more adaptive decision-making under fluctuating field conditions. This integration facilitates more precise data-driven decision-making, diminishing dependence on historical data that may not be pertinent to present circumstances. An automated irrigation system utilising RF-SVM technology for predictive decision-making can effectively address the difficulties of water consumption efficiency in agriculture. Subsequent study may involve evaluating the model across multiple agricultural contexts, such crops with varying water requirements or areas with distinct climatic conditions. The outcomes are anticipated to enhance crop yields while minimising water waste.

A primary challenge in deploying RF-SVM on IoT devices is the substantial computing demands. Consequently, there is a necessity for research aimed at optimising the algorithm to ensure optimal operation on devices with constrained resources, including battery power, memory capacity, and processing speed. This phase is crucial to guarantee the practical implementation of RF-SVM applications in the field, particularly on cost-effective and energy-efficient IoT devices.

Research is required to assess the dangers and reliability of this technology in response to environmental disturbances to enhance confidence in the system. Thorough testing can be conducted to assess the system's capacity to manage device malfunctions, abrupt weather fluctuations, or network interruptions. This evaluation enables the system to be developed for enhanced robustness and adaptability, hence providing stable and consistent performance in practical situations. This research avenue establishes a robust basis for the advancement of intelligent systems utilising RF-SVM and IoT. Emphasising real-time integration, automation, optimisation, and reliability will facilitate the development of efficient, adaptable, and sustainable solutions in water resource management and agriculture.

CONCLUSIONS

The literature review on journals addressing the hybrid integration of RF-SVM, the application of the Internet of Things for real-time data acquisition, and the automation of irrigation systems has yielded several significant discoveries. This analysis identifies research gaps. This study demonstrates that RF-SVM enhances the precision of water demand forecasts, particularly in the domains of irrigation system management, agriculture, and environmental stewardship. Nonetheless, its application remains confined to the realm of real-time data combined with Internet of Things (IoT) devices. The system's scalability, computing efficiency, and reliability are constrained by the dynamic environment.

The analysis results indicate that real-time forecasts using RF-SVM have the highest distribution, at 30%. These findings suggest that additional study is necessary to incorporate this model with real-time data to generate more adaptive solutions. Moreover, numerous domains of the integration of IoT with RF-SVM remain inadequately researched. This indicates the necessity to develop a more efficient and cohesive prediction system. The automation of prediction-based irrigation systems addresses 20% of the observed deficiencies, underscoring the need of developing a system capable of autonomously adjusting irrigation requirements based on predictions produced by RF-SVM. Further constraints, including scalability and computational efficiency (15%) and system risk and reliability (10%), suggest that additional study is required to guarantee the RF-SVM model's applicability at scale with high reliability.

Future research should emphasis the amalgamation of RF-SVM with IoT devices to resolve these challenges. This will facilitate real-time prediction, enhance the flexibility of automated irrigation systems, and optimise the model for greater efficiency on resource-constrained devices. To guarantee the applicability of the developed solution in practical scenarios, it is essential to assess the system's risk and reliability. Consequently, this research is anticipated to substantially enhance environmental sustainability, augment agricultural production, and improve water management efficiency in the future.

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