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Utilization of Smart Technologies Based on Internet of Things and Machine Learning in Energy Management: A Systematic Literature Review

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Abstract

The utilization of smart technologies based on the Internet of Things (IoT) and Machine Learning (ML) has emerged as a crucial strategy for enhancing energy efficiency, particularly in electricity consumption monitoring and management systems. This article presents a Systematic Literature Review (SLR) of scholarly publications discussing the integration of IoT and ML in energy management. The review was conducted using the PRISMA framework, encompassing identification, selection, and analysis of 26 articles published between 2019 and 2024 across various academic databases. The findings indicate that integrating IoT with current sensors, motion sensors, and cloud-based processing, combined with ML algorithms such as Support Vector Machine (SVM), Decision Tree, Random Forest, and Long Short-Term Memory (LSTM), can improve energy efficiency by up to 30% and enable real-time anomaly detection in electricity consumption. Furthermore, such systems facilitate the implementation of automated notifications as early warnings for users. However, most existing studies remain limited to providing information through dashboards that must be monitored manually. In contrast, personalized notifications delivered via instant messaging applications (e.g., WhatsApp, Telegram) or dedicated mobile apps have the potential to engage users more effectively in energy management. Nevertheless, challenges persist in terms of installation costs, data security issues, as well as limitations in infrastructure and human resources. These findings underscore the importance of developing IoT–ML–based energy management technologies that are not only efficient but also sustainable, thereby supporting energy-saving policies and environmental sustainability in the future.

***Keywords**: Anomaly Detection, Energy Efficiency, Internet of Things, Machine Learning, Energy Monitoring System*

1. Introduction

Energy efficiency has become a strategic issue in sustainable development, particularly as the increasing demand for electricity directly impacts operational costs and carbon emissions. In Indonesia, the government has launched several initiatives, such as the "Gerakan Potong 10%" (Cut 10% Movement), to promote electricity savings in residential, commercial, and industrial sectors [1]. In addition, green building standards have been introduced to encourage energy efficiency at the infrastructure design level [2]. The government also supports the transition toward energy-saving technologies by providing tax incentives for environmentally friendly industries [3]. Nevertheless, energy monitoring practices in many institutions remain manual and ineffective, leading to persistent energy wastage.

Advances in the Internet of Things (IoT) have introduced innovative solutions for energy management. IoT enables the real-time collection of electricity consumption data through networks of sensors and smart devices, which can then be continuously monitored and analyzed [4,5]. By connecting various sensors, such as current sensors and motion sensors, IoT systems provide a detailed overview of energy consumption patterns [6,7]. When combined with Machine Learning (ML) algorithms, these systems can not only monitor but also analyze consumption patterns to detect wastage and automatically generate recommendations for energy savings [8,9].

Previous studies have demonstrated that the integration of IoT and ML can increase energy efficiency by 20–30% across different application contexts [8,9]. IoT–ML–based systems offer multiple advantages: automatic anomaly detection, improved user responsiveness through real-time notifications, and the promotion of data-driven energy-saving behavior [10,11]. Several studies in the field of smart buildings confirm that the application of these technologies not only reduces energy consumption but also supports environmental sustainability by lowering greenhouse gas emissions [12,13]. The implementation of ML models for anomaly detection, such as Support Vector Machine (SVM), Decision Tree, and Random Forest, has proven effective in classifying energy consumption patterns and identifying abnormal electricity usage [14–16].

Beyond classical algorithms, developments in deep learning approaches such as Long Short-Term Memory (LSTM) and Variational Autoencoder (VAE) have further enhanced anomaly detection capabilities for complex time-series data [17–19]. Deep learning–based models have shown superior performance in the context of power systems, smart grids, and smart buildings [20–22]. Similar studies in Indonesia also highlight the effectiveness of the LSTM algorithm in detecting anomalies in household electricity consumption [21]. Moreover, research on anomaly detection for information system security emphasizes the relevance of ML approaches in strengthening energy monitoring systems [22].

On the other hand, the integration of IoT–ML has also demonstrated substantial benefits in terms of visualization and user interaction. Recent studies stress the importance of developing web dashboards and mobile applications to present energy consumption data intuitively [23–27]. These applications not only provide information but also serve as educational tools to raise user awareness of energy management. The implementation of automated notifications via email and instant messaging applications adds practical value by preventing unnecessary energy consumption [27]. Thus, IoT–ML functions not only as a monitoring technology but also as a catalyst for behavioral change toward energy efficiency.

In light of these conditions, most previous studies on IoT–ML-based energy management have primarily focused on technical aspects and the provision of information through dashboards or generic alerts. Such approaches require users to continuously monitor dashboards, which is less practical and often fails to engage users actively. In contrast, personalized notification systems delivered through mobile applications or instant messaging platforms (e.g., WhatsApp or Telegram) could provide direct, real-time, and context-aware feedback to users, making energy-saving interventions more effective. Addressing this gap, the present study aims to conduct a systematic literature review on the utilization of IoT and ML in energy management. The review focuses on: (i) mapping IoT components and ML algorithms applied, (ii) identifying achieved energy efficiency outcomes, (iii) highlighting implementation challenges, and (iv) outlining future directions for smart energy systems, with special attention to the potential of personalized notification. Through a Systematic Literature Review (SLR) approach, this article seeks to provide both theoretical and practical contributions to support national energy-saving policies [1–3] as well as the global agenda for energy sustainability [12], [13].

2. Methodology

2.1. Research Design

his article employs a Systematic Literature Review (SLR) approach, guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [28]. This method was chosen because it provides a comprehensive synthesis of prior research while also identifying research gaps for future studies. The SLR process was carried out in four main steps: (i) literature identification, (ii) article screening and selection, (iii) eligibility assessment, and (iv) data synthesis [28]. This approach follows the systematic review guidelines proposed by Kitchenham (2007) [29], which, although originally developed for the field of software engineering, have since been widely adopted in engineering research, including studies on IoT-based energy systems.

2.2. Literature Search Strategy

The literature search was conducted using reputable international databases such as Scopus, IEEE Xplore, ScienceDirect, SpringerLink, with Google Scholar used as a complementary source. The selected publication period was 2019–2024 to capture the most recent trends. Search keywords included: “Internet of Things”, “IoT”, “Machine Learning”, “Energy Efficiency”, “Anomaly Detection”, and “Smart Energy Management”. Boolean operators (AND/OR) were applied to broaden or narrow the search results, for example, “IoT AND Machine Learning AND Energy Efficiency”. This approach is consistent with previous studies on IoT and ML in the context of smart buildings and smart cities [4–7, 12–16].

2.3. Inclusion and Exclusion Criteria

Inclusion criteria:

1. Peer-reviewed articles published in journals or conference proceedings.
2. Studies addressing the integration of IoT and ML in the context of energy management or electricity efficiency.
3. Articles providing quantitative evaluations (e.g., accuracy, precision, recall, F1-score, or energy efficiency percentage).
4. Articles available in English or Indonesian with full-text access.

Exclusion criteria:

1. Opinion papers, editorials, or non-systematic reviews.
2. Articles focusing on non-electrical energy or IoT applications without ML integration.
3. Duplicate articles or studies without full-text availability.

These criteria are consistent with the standard practices of literature reviews in the domain of IoT–ML–based smart energy systems [8–11, 18, 20].

2.4. Study Selection Process (PRISMA)

The article selection followed the PRISMA flow [28]. The initial search yielded 112 articles across various databases. After removing duplicates (54 articles), 58 articles remained for the screening stage. At this stage, 32 articles were excluded due to irrelevance to the research topic. Consequently, 26 articles proceeded to the full-text eligibility assessment, all of which met the inclusion criteria and were analyzed further.

The selection process can be illustrated as follows:

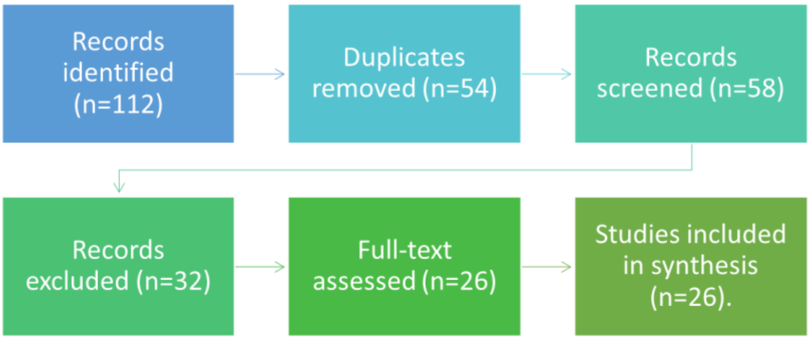

Fig. 1: PRISMA Flow Diagram of the Study Selection Process

2.5. Data Extraction and Quality Assessment

The extracted data from the articles included: (i) application domains (smart building, education, industry, smart grid), (ii) types of IoT sensors (current, motion, smart meters), (iii) system architectures (edge, cloud, hybrid), (iv) applied ML algorithms (SVM, Decision Tree, Random Forest, LSTM, etc.), (v) dataset size, (vi) evaluation metrics (accuracy, precision, recall, F1-score), and (vii) energy efficiency achievements. Quality assessment was carried out using the 2018 version of the Mixed Methods Appraisal Tool (MMAT) [30], which enables evaluation across quantitative, qualitative, and mixed-methods research designs.

2.6. Data Synthesis

The synthesis was conducted in a narrative-descriptive manner, supported by tabulation of the selected studies. The analysis involved grouping the articles based on ML algorithms, types of IoT sensors, and application domains. The results were then compared with similar studies to identify both research consistency and gaps [6,7,10,23–27].

3. Results and Discussion

3.1. Overview of Selected Studies

Out of a total of 112 identified articles, 26 met the inclusion criteria after undergoing the PRISMA selection process [29]. These studies were published between 2019 and 2024, with a significant increase observed after 2021. This trend aligns with the growing affordability of IoT devices and the increasing adaptability of ML algorithms [4–7]. The dominant application domains include smart buildings, educational institutions, households, as well as small- and medium-scale industrial facilities [8–11]. Several studies also highlight the implementation of IoT–ML in the context of smart cities as part of sustainable energy infrastructure [6,7].

3.2. IoT Components in Energy Management

IoT applications in energy management generally involve current sensors (current transformers, smart meters), motion sensors (PIR), and communication modules based on Wi-Fi or MQTT [4,5,10]. The combination of these sensors enables systems to detect electricity consumption patterns based on room occupancy and electrical loads [18]. Edge devices such as ESP32 and Raspberry Pi serve as initial data processors before transmitting information to the cloud for real-time analytics [10,24]. The integration of web-based dashboards and mobile applications allows users to perform monitoring while also receiving automated notifications in the event of anomalous consumption [25–27].

3.3. Machine Learning Algorithms Utilized

Various ML algorithms have been employed to support energy management. Classification algorithms such as Support Vector Machine (SVM), Decision Tree, and Random Forest have proven effective in identifying consumption patterns and detecting anomalies [14–16]. In addition, deep learning approaches, particularly Long Short-Term Memory (LSTM) and autoencoders, have demonstrated superior performance in analyzing time-series data [17–19]. For instance, Guha & Chatterjee (2023) [19] applied an LSTM–Variational Autoencoder to detect anomalies in power systems with promising results. Himeur et al. (2021) [20] also emphasized the effectiveness of deep learning–based methods in identifying abnormal energy consumption in smart buildings.

3.4. IoT Components in Energy Management

The integration of IoT–ML has been shown to improve energy efficiency by 10–30% [4,8,9]. Patel et al. (2022) [4] reported energy savings of up to 20% in smart buildings using IoT–ML–based monitoring systems. Fanti et al. (2024) [9] demonstrated that IoT–ML implementation in educational buildings significantly reduced electricity consumption. Munir et al. (2024) [8] highlighted the potential for energy savings of up to 30% in commercial buildings through the integration of IoT sensors and ML algorithms. These studies affirm that the application of smart technologies fosters the development of a data-driven energy-saving culture [11,20].

3.5. Machine Learning Algorithms Utilized

Despite its potential, IoT–ML implementation faces several challenges. The main obstacles include high initial installation costs, limited interoperability between devices, and network reliability issues [17,18]. Moreover, data security remains a critical concern. Guha & Chatterjee (2023) [19] emphasized the risks of electricity consumption data leakage, while Harjanto et al. (2023) [22] highlighted the need for additional security system integration to support anomaly detection. Digital literacy gaps also present barriers, particularly in educational institutions and small industries [26,27]. These challenges underscore the necessity of enhancing human resource capacity, standardizing devices, and strengthening cybersecurity protections [24,25].

3.6. Summary of Selected Studies

The table below summarizes some of the key studies analyzed.

Table 1: Summary of IoT–ML Literature Studies in Energy Management

Author(s), Year	Application Domain	Sensor/Devices	ML Algorithms	Key Findings
Patel et al. (2022) [4]	Smart Building	Smart meter	General ML	Energy efficiency improved by 20%
Selvaraj et al. (2023) [6]	Smart City	IoT sensors, cloud	Rule-based AI	Real-time monitoring and notifications
Shah et al. (2022) [7]	Smart Building	IoT + sensors	ML integration	Significant energy efficiency improvement
Munir et al. (2024) [8]	Smart Building	Current & motion sensors	SVM, Random Forest	Energy savings up to 30%
Fanti et al. (2024) [9]	Education Sector	IoT sensors, cloud	Deep Learning	Improved energy efficiency in educational buildings
Bin Mofidul et al. (2022) [10]	Industrial IoT	Multi-level sensors	Edge + Cloud AI	Robust anomaly detection
Baswardono et al. (2024) [27]	Web Application	IoT kWh meter	–	Web-based energy visualization

3.7. Discussion

The findings indicate that IoT–ML integration not only enhances technical efficiency but also fosters organizational cultural transformation toward data-driven energy management. Reported efficiency improvements of up to 30% [4,8,9] highlight its effectiveness. However, challenges such as high initial costs, cybersecurity risks, and limited digital literacy demand more comprehensive mitigation strategies [17–19,22,26].

Despite the significant potential of IoT–ML integration, most existing studies have remained limited to providing data visualization through dashboards or generic alerts. This approach requires users to actively access the dashboard to monitor their energy consumption, which is often impractical and reduces user engagement. In contrast, personalized notifications—delivered directly via mobile applications or instant messaging platforms such as WhatsApp or Telegram—could offer real-time, context-aware, and user-specific feedback. Such notifications would not only make the system more interactive but also more effective in shaping energy-saving behaviors. This gap highlights the importance of shifting from passive dashboard-based monitoring toward proactive, personalized feedback mechanisms as a critical direction for future research and system development.

4. Conclusion

This systematic literature review has examined 26 studies published between 2019 and 2024 on the integration of Internet of Things (IoT) and Machine Learning (ML) for energy management. The findings confirm that IoT–ML systems can significantly enhance energy efficiency, with improvements ranging from 10% to 30% across domains such as smart buildings, households, educational institutions, and small industries. By combining IoT sensors (e.g., current sensors, motion sensors, smart meters) with algorithms including SVM, Decision Tree, Random Forest, and LSTM, existing studies have demonstrated effective anomaly detection, consumption pattern analysis, and real-time monitoring. These outcomes illustrate the potential of IoT–ML to contribute not only to technical efficiency but also to global sustainability goals.

Nevertheless, this review highlights a critical research gap: most existing systems remain limited to dashboard-based monitoring and generic alerts, which require users to actively check their consumption data. Such passive mechanisms are less practical and may reduce user engagement in energy-saving practices. In contrast, personalized notification systems, delivered via mobile applications or instant messaging platforms such as WhatsApp or Telegram, could provide proactive, context-aware, and user-specific feedback. By shifting from dashboard visualization to personalized notifications, IoT–ML systems can more effectively support behavioral change and foster a data-driven energy-saving culture.

Future research should therefore focus on embedding personalized notification features into IoT–ML energy management systems, while also addressing persistent challenges including installation costs, device interoperability, cybersecurity risks, and digital literacy gaps. Emerging approaches such as edge computing and federated learning may further strengthen scalability, privacy, and efficiency. For policymakers, these findings suggest the importance of incentives and regulatory support to promote the adoption of personalized, user-centered energy management technologies. In conclusion, IoT–ML should be seen not only as a technological enabler for efficiency, but also as a practical tool to directly engage users in sustainable energy practices through personalized feedback and proactive interventions

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