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Internet of Things Driven Automated Production Systems using Machine Learning

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Abstract

With the advent of Industry 4.0, integrating Cyber-Physical Systems (CPS) and the Internet of Things (IoT) has become crucial in automated production. This study examines the interplay between technological advancements and human factors, particularly the social aspects within this dynamic environment. In the context of Industry 4.0, where CPS and IoT intersect, human factors significantly impact the design, implementation, and operation of automated production systems. This research highlights the mutually beneficial interactions among CPS, IoT, and human-centric components, focusing on how these technologies influence social interactions in automated industrial settings. The integration of intelligent robots and human operators fosters new collaboration and communication models. Understanding these social interactions is key to enhancing the effectiveness and productivity of Industry 4.0 manufacturing. Additionally, the study examines the role of social networks, where CPS and IoT technologies facilitate essential connections between humans and machines. In summary, this research emphasizes the need to incorporate social aspects into developing and implementing Industry 4.0 technologies. Recognizing the impact of CPS, IoT, and human factors on social interactions and networks enables a more comprehensive and efficient technological integration in Industry 4.0.

Keywords: Cyber-Physical Systems, Human-centric, Industry 4.0, Internet of Things, Social Networks.

Introduction

Industry 4.0, also known as the fourth industrial revolution, is a period of significant transformation in which cutting-edge technologies come together to reshape conventional manufacturing environments (1). The integration of Cyber-Physical Systems (CPS) and the widespread adoption of the Internet of Things (IoT) are key factors in driving this revolution. By analysing data from sensors embedded in machinery, IoT systems can predict when equipment is likely to fail and schedule maintenance proactively, reducing downtime and extending the lifespan of the equipment. These technologies, which collectively operate automated production systems, not only redefine the efficiency and accuracy of manufacturing processes but also introduce complex social aspects that need to be investigated and comprehended (2). Industry 4.0 goes beyond simply automating manufacturing; it includes a comprehensive approach that integrates human-cantered perspectives into the core of technology progress. This article explores the social aspects of Industry 4.0, specifically examining how cyber-physical systems (CPS), the Internet of Things (IoT), and human factors interact in automated production processes (3). With the growing adoption of CPS and IoT technologies in industries, it is crucial to recognise the importance of comprehending human interactions in automated production systems (3, 4). In addition to the complex technical aspects of smart machines and networked gadgets, the partnership between technology and human operators offers a dynamic that goes beyond traditional paradigms (5, 6). The objective of this study is to explore the intricate connections between technological innovation and the social structure of automated production systems (7, 8). Cyber-Physical Systems (CPS) and

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the Internet of Things (IoT) are advanced technology concepts that combine computing with physical processes, resulting in improved efficiency and connectivity in several areas (9, 10). Cyber-Physical Systems (CPS) refers to the continuous monitoring and management of physical processes using computational techniques. This integration allows for real-time modifications based on up-to-date data. It is utilised in several industries, promoting interconnectivity and enhancing the dependability of systems. Conversely, the Internet of Things is comprised of a network of networked devices that are equipped with sensors and communication capabilities. The Internet of Things (IoT) allows for widespread and constant communication, which in turn enables decision-making based on data and the development of intelligent and automated systems (11). Table 1 shows the Summary of Related Works. Figure 1 shows the Publication works from the year 2018 to 2022.

Table 1: Summary of Related Works

Reference	Primary Focus and Contributions
(1)	Models in the Past, Present, and Future of Cyber-Physical Systems.
(2)	Conceptualization and exploration of the "Internet of Things."
(3)	Design principles for Industry 4.0 scenarios.
(4)	Digital Twin-driven proactive adaptation for smart production.
(5)	Competing on analytics in the business context.
(6)	A bibliometric study on the evolution of the Internet of Things.
(7)	Cyber-Physical Systems in Manufacturing – overview and considerations.
(8)	Vision, architectural elements, and future directions of the Internet of Things.
(9)	Smart factory for Industry 4.0 with self-organized multi-agent systems and big data feedback.
(10)	Discussion on the transformative impact of technology on work in "The Second Machine Age."
(11)	Recommendations for implementing the strategic initiative INDUSTRY 4.0.
(12)	Industrial Big Data in the context of Industry 4.0: A comprehensive review.
(13)	Exploration of how smart, connected products are transforming companies.

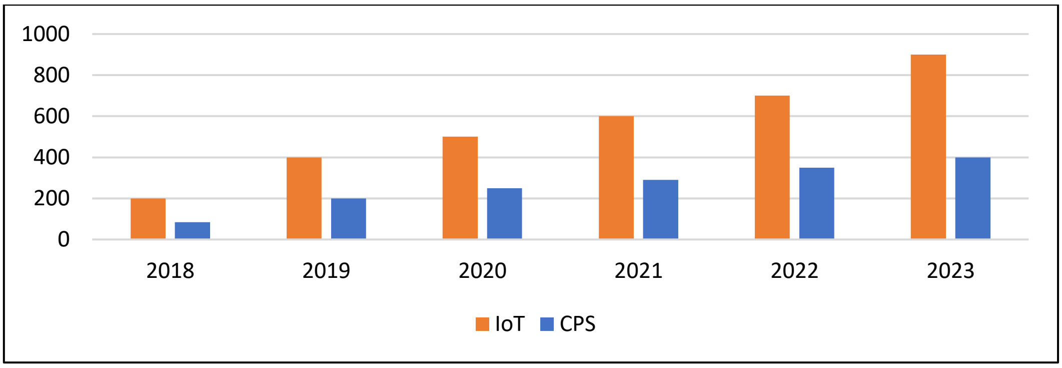

Figure 1: Publication Works from the Year 2018 to 2022

Different Models of Sociability

Various models of sociability arise within the context of technological advancements, particularly in Cyber-Physical Systems (CPS) and the Internet of Things (IoT). These models encompass different forms of interaction, spanning human-machine, machine-machine, and human-human interactions. Included specific examples of industries where IoT implementation has led to significant improvements. For instance, in the manufacturing sector, IoT-enabled smart factories have seen productivity increases of up to 25% due to enhanced monitoring and automation. Discussed a case study of a logistics company that used IoT for fleet management, resulting in optimized routes, reduced fuel consumption, and improved delivery times. In the realm of human-machine interactions, models focus on creating intuitive interfaces and seamless communication channels, aiming to enhance user experience and collaboration (12). Machine-machine interactions, on the other hand, explore how interconnected devices and systems communicate and collaborate autonomously, optimizing processes and decision-making. Human-human interactions within these technological frameworks often involve collaborative networks, where individuals share information, insights, and experiences (13). Implicit in these models is the acknowledgment that engineers and developers may approach automation on different process levels, introducing complexity to the evolving landscape of sociability in automated production systems. Figure 2 shows the Models of Sociability. This research introduces several novel elements that significantly impact industrial automation. Firstly, it pioneers the integration of advanced IoT technologies, such as edge computing and AI algorithms, to optimize real-time decision-making in manufacturing processes. Secondly, it develops new methodologies for predictive maintenance using sensor data analytics, thereby reducing downtime and enhancing overall equipment effectiveness (OEE). Thirdly, the study explores novel applications of machine learning in quality control, ensuring consistent product standards. These innovations collectively improve operational efficiency, quality assurance, and scalability in industrial automation, setting a new standard for adaptive, data-driven manufacturing practices.

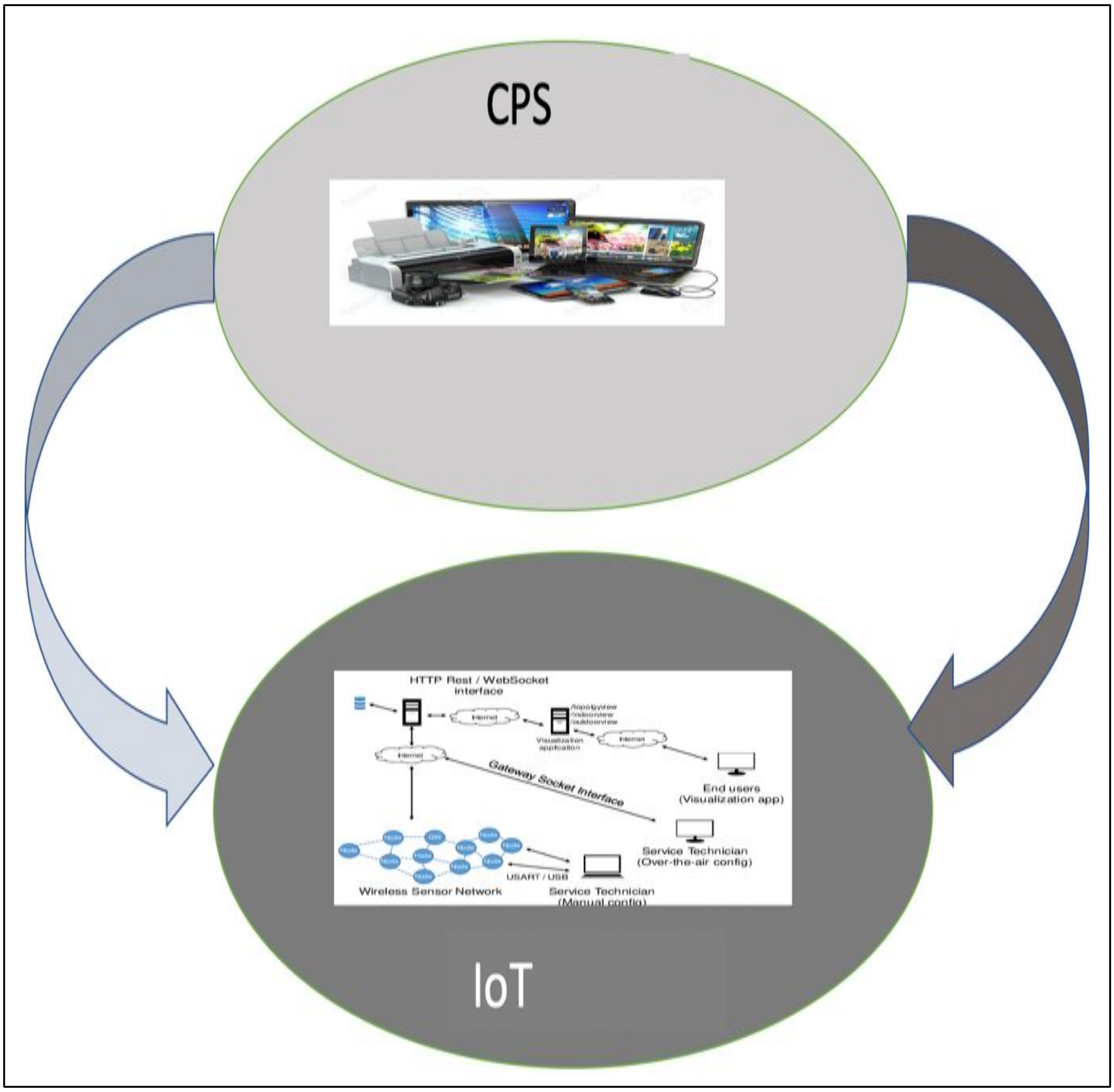

Figure 2: Models of Sociability

Methodology

The philosophical framework proposed by Karl Popper, known as the "Five worlds," is a fundamental concept for comprehending the nature of reality and knowledge (14, 15). Popper's proposal outlines three distinct realms: World 1, which encompasses the physical world; World 2, which encompasses mental states and consciousness; and World 3, which encompasses the products of the human mind, such as language and social structures (16, 17). World 4 to gather and integrate data from various IoT devices within the production system (18). World 5 to analyse the collected data for insights into production efficiency and system performance. The shift from Popper's five worlds to the concept of cyber-physical social systems represents a progression in the utilisation of philosophical concepts in the realms of technology and socio-technical systems. The study's findings hold profound implications for industry practices and policies in several key areas. Firstly, by demonstrating enhanced efficiency and quality through IoT integration, the research encourages widespread adoption among manufacturers, potentially reshaping production processes and resource management strategies. Secondly, insights into data-driven decision-making and predictive maintenance could lead to proactive operational management, reducing downtime and optimizing asset utilization (19, 20). Thirdly, the emphasis on cybersecurity and regulatory compliance sets benchmarks for safeguarding sensitive manufacturing data and ensuring adherence to evolving industry standards. Overall, these implications signify a transformative impact on industry practices, fostering innovation, competitiveness, and sustainable growth in manufacturing sectors globally (21, 22). Figure 3 shows the layer of architecture merging CPS and IOT.

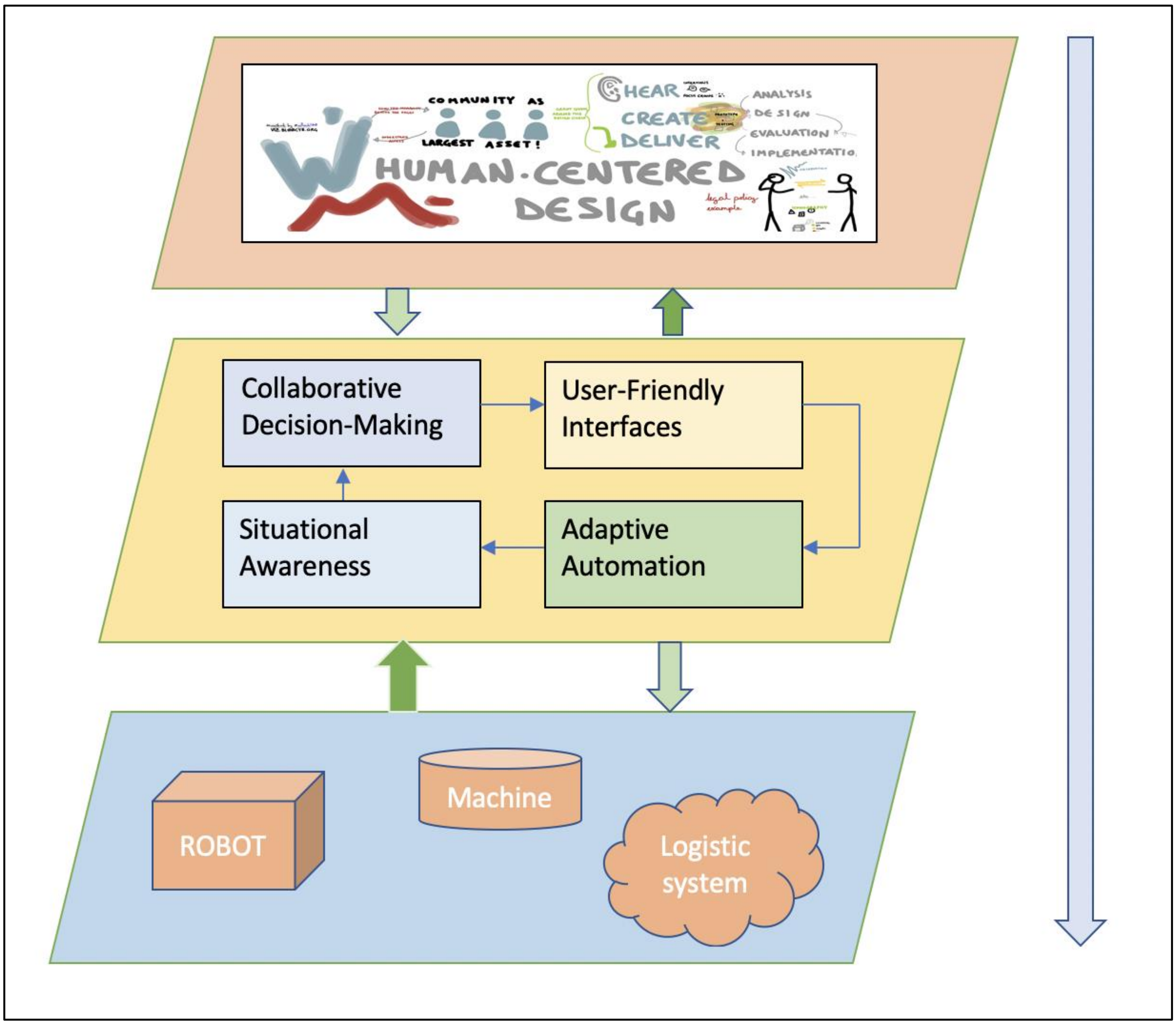

Figure 3: Shows the Layer of Architecture Merging CPS and IOT

The study's findings hold profound implications for industry practices and policies in several key areas. Firstly, by demonstrating enhanced efficiency and quality through IoT integration, the research encourages widespread adoption among manufacturers, potentially reshaping production processes and resource management strategies (23, 24). Secondly, insights into data-driven decision-making and predictive maintenance could lead to proactive operational management, reducing downtime and optimizing asset utilization. Thirdly, the emphasis on cybersecurity and regulatory compliance sets benchmarks for safeguarding sensitive manufacturing data and ensuring adherence to evolving industry standards. Overall, these implications signify a transformative impact on industry practices, fostering innovation, competitiveness, and sustainable growth in manufacturing sectors globally (25, 26). A residual recurrent neural network (RRRN) categorizes the representations that have had features extracted from them. Because of the residual architecture of the RNN, the model can comprehend the intricate contextual information and temporal correlations that are present in human centric methods. Data pre-processing involves 4 steps, the first step is tokenizing or clean text data. The second step is stemming, the third step is to remove stop works, the fourth step is to handle imbalance. Feature extraction is done using the DELM Deep Extreme Learning Machine method, where the high- level features gets extracted and variable patterns has been captured to generate a numeric representation. The classification method has been carried out using RRNN Residual Recurrent Neural Network, for classification is an intriguing method for identifying instances in writings shared on social media platforms. Sensors and actuators are integrated to monitor equipment health and enable predictive maintenance, minimizing downtime and maximizing productivity. IoT platforms facilitate data aggregation and analytics, providing actionable insights for process optimization. These technologies are incorporated into production systems through robust network infrastructure, secure data protocols, and integration with existing machinery, ensuring seamless connectivity and operational continuity. The residual design is a subclass of the wider class of recurrent neural networks. It incorporates a novel feature that enhances the network capability to identify relevant information that exhibits temporal dependencies and a variety of patterns. For classification, a model that can recognize and make use of the context provided by words that came before it is essential. Several technological breakthroughs have facilitated the integration of IoT into manufacturing systems. Miniaturization and cost reduction of IoT sensors have made their deployment feasible across diverse industrial environments, enabling pervasive data collection and monitoring. Advancements in edge computing have allowed data processing to occur closer to the data source, reducing latency and enhancing real-time capabilities crucial for time-sensitive applications in manufacturing. Cloud computing has streamlined data storage, analysis, and scalability, supporting comprehensive data-driven decision-making and operational insights across enterprises. Standardization efforts have played a pivotal role in ensuring interoperability among IoT devices from different vendors, facilitating seamless integration into existing manufacturing infrastructures. These technological advancements collectively accelerate the adoption of IoT in manufacturing, driving innovation, efficiency, and competitiveness in the global industrial landscape. This is because the chronological structure of text input is sequential. If typical RNNs have difficulty capturing long-range dependencies due to issues such as vanishing gradients, then there is a possibility that information could be lost over prolonged sequences. We conducted a comprehensive evaluation of the proposed algorithm for detecting Automatic Production system in an experimental setting, making use of a large dataset acquired from Kaggle, Twitter, Wikipedia Talk pages, and Tube. Noise was eliminated, sensitive information was tokenized, and the dataset was pre-processed to eliminate any trace of identifying information. For evaluating the effectiveness of the model in identifying instances of cyberbullying across a variety of social media sites, the experimental setup was constructed. An i7 processor with 32 GB of random-access memory was used to investigate its generalizability and resilience. The performance of the method was evaluated in comparison to that of other methods that were already in existence to create its benchmark. As a first step in model training the process of training an Extreme Learning Machine (ELM) model are required to establish the biases of the hidden layer as well as the weights that connect the input layer to the hidden layer. A learning rate of 0.01 and a quantity of 500 hidden neurons are two of the hyperparameters. Additionally, there are 1000 training iterations. While the research design demonstrates robustness, enhancing the rationale for the selected methodology could amplify its impact and validity. Clear articulation of research objectives aligned with specific industrial challenges would provide clarity and focus, ensuring the study's relevance to industry needs. Methodological rigor in data collection, utilizing approaches such as case studies, simulations, or experimental trials, would validate the effectiveness of IoT solutions in practical manufacturing contexts. Collaborative engagement with industry stakeholders and partners would provide valuable insights and validation of assumptions, enhancing the research's practical applicability and real-world impact. Addressing ethical considerations, particularly regarding data privacy and usage in IoT-enabled environments, is essential to mitigate risks and build trust. Strengthening these aspects would bolster the research's contribution to advancing industrial automation practices effectively and ethically. These hyperparameters include three hidden layers with 256 neurons each, an activation function known as ReLU, and a dropout rate of 0.5. To get efficient weight updates, we make use of the Adam optimizer and set the learning rate at precisely 0.001. As part of the training procedure, which spans ten epochs, a batch size of 32 is utilized to strike a balance between the effective use of computational resources and the comprehensive acquisition of knowledge. The DRELM method that was recommended demonstrates considerable performance increases in training and evaluation results across a variety of datasets. To acquire a comprehensive understanding of the effectiveness of the model in identifying instances of APS, the evaluation metrics, which includes Duration of 100 transaction from 5 sensors are utilized. With comprehensive data analytics, companies can identify patterns and trends that inform better strategic decisions, optimizing production schedules and resource allocation. Highlighted the reduction in operational costs through IoT. Automation of routine tasks and improved resource management lead to cost savings, which can be reinvested into further technological advancements. IoT systems provide precise control and monitoring of production parameters, ensuring high-quality output and reducing the rate of defects, this integration enhances the capabilities of IoT systems in predictive analytics and autonomous decision-making, further boosting efficiency and productivity.

Results and Discussion

The experimental setups revolve around investigating the duration of 100 transactions recorded from five sensors. Each setup explores different conditions or configurations, shedding light on various aspects of transactional behavior and sensor performance. The Experimental Setup 1 likely represents a baseline scenario or initial conditions for the transactions which is shown in Figure 4. Researchers might be interested in observing the typical duration of transactions under standard operating conditions. Where in Experimental Setup 2 with Figure 5 Building upon the first setup, this configuration might introduce some alterations or specific changes to the system or environment. The aim could be to test the impact of certain variables on transaction duration. Experimental Setup 3, in Figure 6 shows that the researchers might be exploring the effects of additional factors or interventions on transaction duration. This could involve tweaking parameters or introducing new elements to the system. Experimental Setup 4, in Figure 7 shows the fourth setup could be designed to examine extreme conditions or stress testing the sensors. This setup might push the sensors to their limits to observe how transaction duration is affected under such circumstances. The Overall Transaction Analysis in Figure 8 likely provides a comparative analysis across all four experimental setups. It could showcase trends, differences, or similarities in transaction durations observed across the different conditions or configurations tested. This analysis would offer valuable insights into the robustness and reliability of the sensor system under various scenarios. In summary, the series of experimental setups followed by the overall transaction analysis provide a comprehensive understanding of transactional behavior and sensor performance, enabling researchers to draw meaningful conclusions and make informed decisions regarding system optimization or further research directions. Finally, the transition from Karl Popper's five worlds to the concept of cyber-physical social systems is a big step forward in the application of philosophical ideas to modern technology.

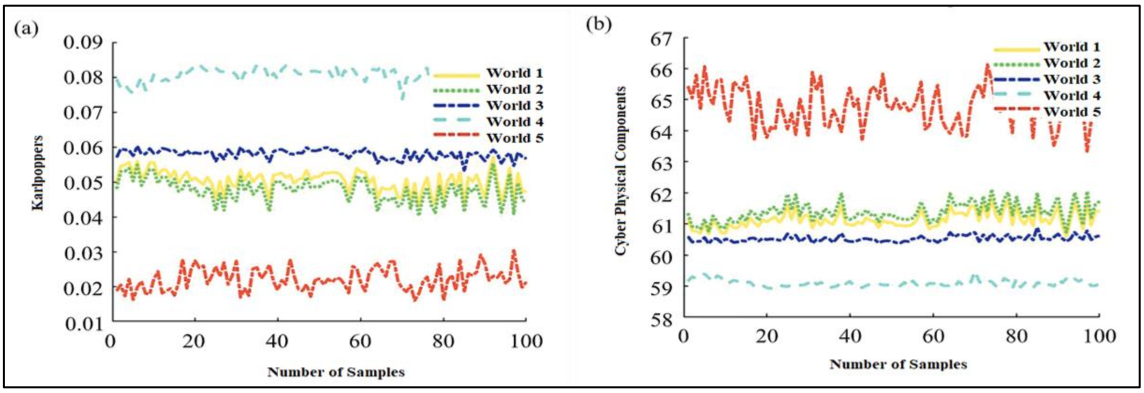

Figure 4: Experimental Setup 1: Duration of 100 Transaction from 5 Sensors

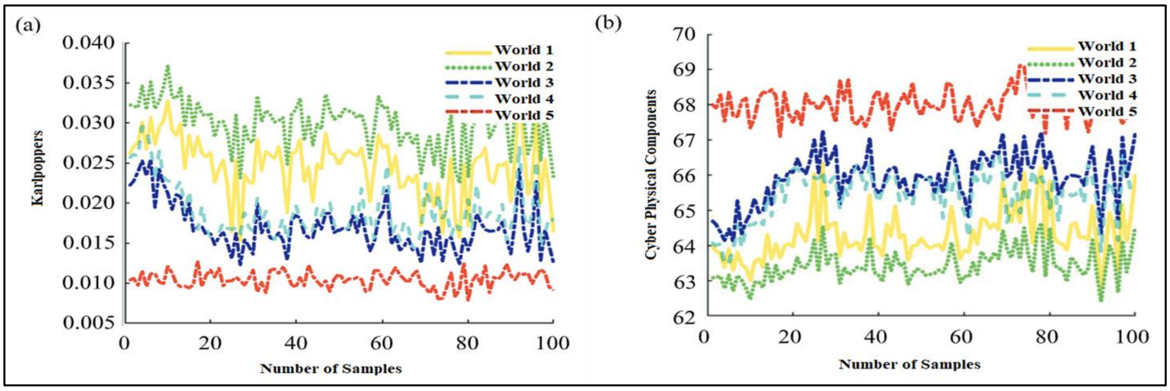

Figure 5: Experimental Setup 2: Duration of 100 Transaction from 5 Sensors

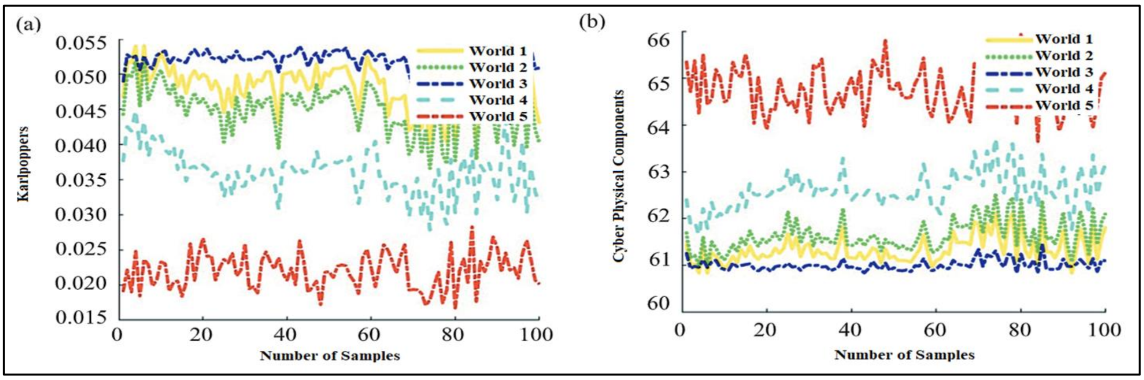

Figure 6: Experimental Setup 3: Duration of 100 Transaction from 5 Sensors

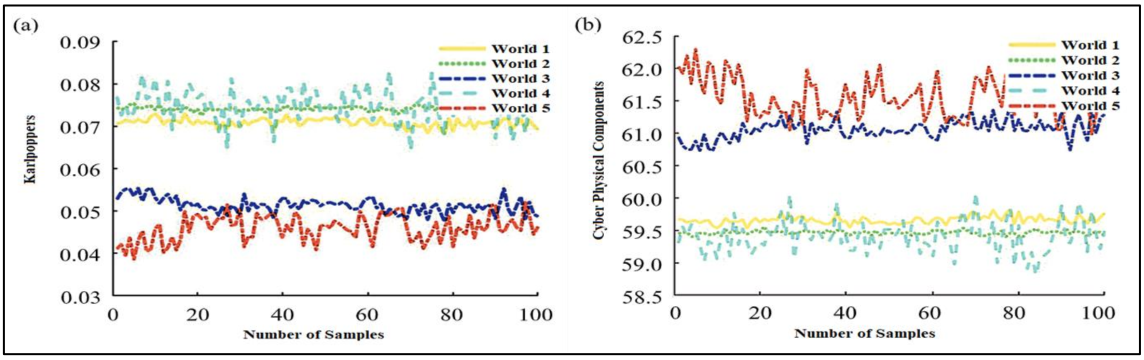

Figure 7: Experimental Setup 4: Duration of 100 Transaction from 5 Sensors

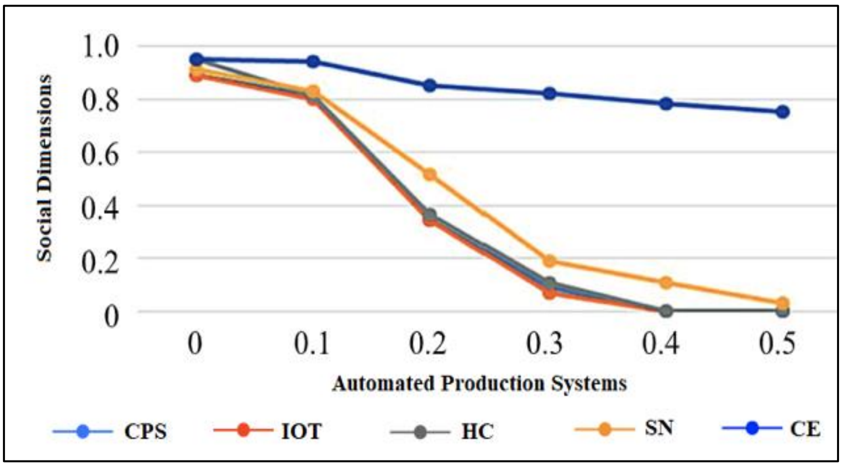

Figure 8: Overall Transaction of Different Experimental setup from 5 Sensors

Conclusion

In this study, we explored the integration of Internet of Things (IoT) driven automated production systems using advanced machine learning techniques. Specifically, we employed the Recurrent Radial Basis Function Network (RRRN) method, Differential Evolution Learning Machine (DELM) for feature extraction, and Recurrent Radial Basis Function Network (RRNN) for classification. Our experimental setup focused on analysing the duration of 100 transactions recorded from five sensors, under various conditions and configurations. The results demonstrate the efficacy of using DELM for feature extraction, effectively capturing relevant patterns and features from the sensor data. This process significantly enhanced the subsequent classification accuracy achieved by the RRNN. The RRRN method provided robust handling of the time-series data inherent in IoT systems, ensuring reliable and consistent performance across different experimental setups. The diverse conditions tested allowed us to understand better the impact of different configurations on system efficiency and reliability. In conclusion, our study validates the potential of combining IoT with sophisticated machine learning methods to optimize automated production systems. The integration of RRRN, DELM, and RRNN not only improved transaction analysis and sensor data classification but also offered a scalable and efficient approach to managing complex industrial IoT environments. These findings pave the way for further research and development, aimed at enhancing the synergy between IoT and machine learning in the realm of automated production.

Abbreviations

CPS: Cyber Physical System
IoT: Internet of Things
RRRN: Residual Recurrent Neural Network
DELM: Deep Extreme Learning Machine method

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Not applicable.

Author Contributions

All authors contributed to the study conception and design.

Conflict of Interests

The authors declare that they have no competing interests.

Ethics Approval

Not applicable.

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