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AI-Driven Autonomous Decision Intelligence for Smart Food Manufacturing Cyber-Physical Systems

Shajahan Basheer[1, *], Anusha A[2], Likitha N[3]

[1 2 3] School of Computer Science and Engineering, Jain (Deemed-To-Be University) Bangalore, India. *Bshajahan001@gmail.com, juug24btech23543@jainuniversity.ac.in, juug24btech19439@jainuniversity.ac.in*

*** Corresponding author.**
E-mail: *Bshajahan001@gmail.com*

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ABSTRACT

The food manufacturing industry is undergoing a rapid transformation through the adoption of Industry 4.0 technologies, which include Cyber Physical System (CPS), Artificial Intelligence (AI) and Industrial Internet of Things (IIOT). Despite of these developments, modern food manufacturers continue to face challenges which are related to quality consistency, food safety assurance, process optimization and real-time decision making. The large amount of data generated by numerous sensors and production systems often remain underutilized because of the limited intelligent decision-making capability of the system. Simultaneously, the manufacturers identify production inefficiencies, resource wastage, increased operational cost and difficulties in maintaining a uniform product quality. To address these challenges, Autonomous System, Artificial Intelligence (AI) and Decision Intelligence are introduced as transformative technologies which are capable of converting a raw data into an actionable insight. This process includes by integrating the Machine Learning, Computer Vision and Predictive Analytics enables real-time monitoring, predictive maintenance and adaptive process control. Therefore, these capabilities support a data-driven decision making, improve the resource utilization and enhance food-safety and sustainability. Furthermore, the autonomous system can dynamically respond to the changing production conditions enabling a flexible manufacturing operation. This paper explores the role of AI-driven autonomous system and decision intelligence in advancing smart food manufacturing CPS. It discusses all the key enabling technologies, implementation challenges and industrial application while highlighting their potential to transform traditional manufacturing environments into an intelligent and a self-optimizing system. This paper aims to provide an insight into the development of efficient, reliable and a sustainable next-generation food manufacturing ecosystem.

1. Introduction

The first sentence should start here [1]. Should have "6pt" spacing after section header. The indent of the first line of paragraph should be 0.25cm. Content in body paragraph should be written with the Font style: Palatino Linotype; Font size: 10; Paragraph: Justify; Line spacing: 1.0. **For example:** The last few decades have witnessed vast research on new types of heat transfer fluids, namely nanofluids.

The food manufacturing industry is undergoing a significant transformation driven due to the increasing demand for safe, high-quality, sustainable, and efficiently produced food products. The food manufacturing industry plays an important role in today's world, as the global population continues to increase, the rapid population growth also increases which has created a greater demand for the efficient, sustainable, and high-quality food production. In addition to these the consumers are increasingly expecting food products that ensure a quality, safety, and a sustainable throughout the manufacturing process. The Traditional food manufacturing methods primarily rely on manual operations and human intervention. Although these methods have been widely adopted for many years, they often result in inconsistent product quality, human errors, higher fault rates, and reduced operational efficiency. Furthermore, the traditional manufacturing systems provide a limited real-time monitoring and decision-making capabilities, making it difficult to respond effectively to dynamic production conditions [1][2].

Therefore, the emergence of the Industry4.0 has significantly transformed the manufacturing systems by introducing an intelligent and connected technologies into a conventional production environment. The adoption of Industry 4.0 technologies in food manufacturing has improved automation, operational efficiency, productivity, and process reliability. These advancements have enabled manufacturers to optimize the production processes while maintaining consistent food quality and safety. Some of the key technologies of Industry 4.0 include Cyber-Physical Systems (CPS), which integrate physical manufacturing` processes with computational systems to enable real-time monitoring and control [10][12]. The Industrial Internet of Things (IIoT) facilitates continuous data collection through interconnected sensors, allowing manufacturers to monitor production parameters and automate manufacturing operations. Artificial Although these emerging technologies such as Artificial Intelligence (AI), Cyber-Physical Systems (CPS), Industrial Internet of Things (IIoT), and Machine Learning (ML) have been widely adopted in food manuf Intelligence (AI) supports in intelligent prediction and accurate decision-making by analyzing large volumes of production data. Furthermore, Machine Learning (ML) models such as Support Vector Machine (SVM), Decision Tree, and Random Forest are widely used to identify patterns, predict equipment failures, and support intelligent decision-making. Hence, the integration of these emerging technologies has led to the development of smart food manufacturing systems which reduce human intervention, improve the automation, enhance production efficiency, and ensure the delivery of safe, high-quality, and sustainable food products. [3][10].

The rapid advancement of Industry 4.0 technologies has created new opportunities for the developing intelligent and an autonomous food manufacturing system. Simultaneously, the food manufacturing industry has become one of the important sectors for adopting the smart technologies to improve productivity, operational efficiency, and product quality. The adoption of these emerging technologies has enabled the manufacturers to enhance production processes while meeting the increasing consumer demand for safe, high-quality, and sustainable food products.

They are often implemented as an independent solution rather than a fully integrated intelligent system. As a result, many existing manufacturing systems are unable to achieve a seamless communication, coordinated decision-making, and a fully autonomous operation. Integrating all these technologies into a unified framework has been one of the potential ways to significantly improve the manufacturing efficiency, operational reliability, and customer satisfaction.[1][17].

A major research gap identified from the existing literature is that most studies primarily focus on individual applications such as automated quality inspection, predictive maintenance, IoT-based monitoring, or AI-based prediction. However, only a limited number of studies have explored the integration of these technologies into a comprehensive end-to-end intelligent manufacturing framework which allows a sensing, analysis, decision-making, autonomous execution, and continuous learning. Therefore, this paper proposes an integrated AI-driven Cyber-Physical System framework which allows the framework of IIoT, Artificial Intelligence, Machine Learning, Decision Intelligence, and Autonomous Systems into a unified architecture capable of real-time monitoring, intelligent decision-making, autonomous execution, and continuous feedback. The proposed framework aims to enhance production efficiency, improve food quality and safety, optimize resource utilization, and contribute to the development of sustainable smart food manufacturing systems. [3][17].

The primary objective of this paper is to present an AI-driven Cyber-Physical System (CPS) framework for smart food manufacturing by integrating the Industry4.0 technologies into an intelligent architecture. This chapter utilizes all the existing technologies such as Artificial Intelligence (AI), Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), and Machine Learning (ML), and integrates them into a unified intelligent system which enables a complete workflow from real-time data collection to intelligent decision-making. This integrated framework supports the production of high-quality food products, while enhancing the operational efficiency and by meeting the customer expectations

Furthermore, this paper majorly identifies the major limitations reported in the existing studies, which includes the limited automation, predictive analytics, and the intelligent decision-making. The proposed framework aims to address these limitations by developing a fully integrated smart manufacturing system that combines the sensing, analysis, decision-making, and autonomous control within a single architecture.

Fig. 1. Evolution of the Technologies

2. Literature Review

The emergence of the Industry4.0 technologies has led to an important transformation from the Traditional manufacturing system to Smart Food Manufacturing Industry. The integration of the emerging technologies such as Artificial Intelligence (AI), Industrial Internet of Things (IIoT), and Cyber Physical System has enabled an improved production, quality assurance, automated and real-time decision-making. Researchers have explored various approaches for the development of the Smart Food Manufacturing system by combining the sensing technologies and intelligent automation. This paper presents a comprehensive review of the existing research which are related to AI-driven food manufacturing, IIoT-enabled industrial systems, CPS-based architecture digital twins and automated decision making.

2.1 Artificial Intelligence

Mavani et al. (2022) reviewed the application of the Artificial Intelligence (AI) in the food industry by reviewing various AI techniques such as machine learning, deep learning and computer vision. The paper highlights the use of AI in food quality, safety monitoring and optimization. The authors concluded that AI improves productivity, reduces the operational cost and enhances decision-making. However, they have also identified specific challenges related to data quality, implementation costs and integration of AI with the existing food manufacturing systems.[1]

Canatan et al. (2025) reviewed the current state of the AI applications in the food manufacturing industry and has discussed the future opportunities of the Artificial Intelligence. The study has explored the AI-based solutions for predictive maintenance and production monitoring by using advanced techniques such as advanced machine learning and deep learning techniques. The author highlights the point that AI can enhance the manufacturing efficiency, product consistency and helps in automated decision-making. The also pointed the point that the future research should focus on the integration of the Industry4.0 technologies.[17]

2.2 Industry Internet of Things (IIoT) in Smart Food Manufacturing

Hassoun et al. (2024) has explored the transformation from the Industry4.0 to Industry 5.0 by identifying all the key technologies. The study has discussed the role of the advanced technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and digital twin in developing smart and sustainable food manufacturing systems. The authors have highlighted an important point that the Food Industry 5.0 focuses not only on the automation, but also on the human and machine collaboration. However, the study has identified some of the challenges such as high implementation costs, data security risks and effective integration.[25]

Sing et al. (2025) has presented a systematic review on the advancement of food systems through the Industry5.0 technologies, focusing mainly on the smart technologies. The study has analyzed the application of various fields such as AI, IoT and intelligent systems in improving food production. The authors have highlighted a point that the Industry5.0 has enabled a more sustainable and a human-centric manufacturing system. However, they have identified some of the challenges such as interoperability, scalability and the development of the integrated frameworks by combining multiple technologies.[30]

2.3 Cyber Physical Systems (CPS) in Smart Manufacturing Systems

Oks et al. (2024) has presented a comprehensive review of Cyber Physical System, which is one of the core technologies of the Industry4.0. The study has explained how the CPS integrates with the physical manufacturing components with the computational intelligence and data-driven control mechanisms which enables and automated operations. The authors have highlighted an important point of CPS which is real-time monitoring and autonomous decision-making within smart manufacturing systems. However, they have also identified some of the challenges such as system complexity and cybersecurity risks.[10]

Andronie et al. (2021) has conducted a systematic literature review on a smart, sustainable and sensing technologies. The study has explained the integration of the sensors, IoT technologies, and automation techniques to develop an intelligent system. The authors have highlighted a point that the CPS-based systems help in improving the production efficiency and real-time process control. However, there are some challenges identified such as implementation costs and automated-integration frameworks to support a smart manufacturing systems.[12]

2.4 Digital Twin

Huang et al. (2024) has reviewed the implementation of the digital twin technology in the food supply chain. The study explains how the digital twins can create a virtual representation of the physical systems, by integrating the real-time data from IoT sensors and simulation models. The authors have highlighted a point that the digital twin can enhance the predictive decision-making and optimize the resource utilization. However, they have identified some of the challenged such as real-time synchronization, implementation cost and system complexity.[19]

Azeta et al. (2026) have presented a comprehensive review of the Artificial Intelligence (AI) and predictive maintenance in robotic systems. The study has discussed how the AI algorithms, machine learning algorithms and robotic technologies can predict the equipment failure and reduce downtime. The authors have highlighted a point the AI-driven predictive maintenance supports the autonomous manufacturing by enabling an early fault detection. However, some of the challenges such as model reliability and integration of AI-based maintenance system with the existing manufacturing systems [29].

Table 1 Literature Survey

Authors	Technology/ Methodology	Key Findings	Research Gap
Mavani et al. (2022)	AI, ML, Deep Learning and	AI improves the food quality inspection,	The lack of the integrated AI-driven manufacturing frameworks

	Computer Vision	safety monitoring and the optimization	
Canatan et al. (2025)	AI, ML, Deep Learning	AI enhances the predictive maintenance and production monitoring	The Integration of the AI with CPS and IIoT
Frankó et al. (2022)	Machine Learning, IIoT	ML improves the production quality and the intelligent monitoring	The lack of integrated AI-enabled IIoT architecture
Vedantam et al. (2024)	IIoT, sensors and cloud	IoT enables a real-time monitoring and improved food quality	The lack of a secure IIoT-enabled manufacturing system
Oks et al. (2024)	Cyber Physical System	CPS enables intelligent monitoring and autonomous control	The integration of the AI-enable CPS architecture
Andronie et al. (2021)	CPS, IoT and Smart Sensors	The smart sensing improves the production efficiency	There is no unified CPS-based framework
Huang et al. (2024)	Digital Twin	Digital Twins improve the monitoring and the resource optimization	There is a lack of the AI-enabled Digital Twin integration
Azeta et al. (2026)	AI, Robotics	The AI-based predictive maintenance reduces the equipment downtime	The lack of integration of the Autonomous predictive and the maintenance framework
Hassoun et al. (2024)	Industry 5.0, AI, IoT	The Human Centric and Sustainable manufacturing	The lack of the end-to-end industry 5.0 framework
Sing et al. (2025)	Industry 5.0, AI, IoT	The smart technologies improve the sustainability and the resource optimization	The lack of integrating of the AI-driven food manufacturing architecture.

3. Current Challenges in Smart Food Manufacturing:

3.1 Quality Assurance and Food Safety

Maintaining food quality and safety is one of the most critical challenges in the modern food manufacturing system, as the consumers demand for safe, high-quality, and contamination-free food products are increasing. Consequently, ensuring the consistent food quality, it has become a major objective of the smart food manufacturing systems. The Manufacturers are required to maintain a high production standard while complying with food safety regulations and meeting customer expectations.

Although, these emerging technologies have significantly improved the manufacturing processes, several challenges still exist due to the lack of complete integration among the intelligent systems. Existing manufacturing systems may still involve manual operations, inconsistent product quality, delayed defect detection, and limitations in achieving accuracy and a highly reliable decision-making capability. These challenges can lead to customer dissatisfaction, increased food waste, production delays, and financial losses for manufacturing industries. Furthermore, the failures in maintaining food quality and safety may affect the product reliability, regulatory compliance, and the overall reputation of food manufacturing organizations.

Therefore, there is a need to integrate the emerging technologies of Industry 4.0 into a unified intelligent manufacturing system. The integration of the Artificial Intelligence (AI), Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), and the Machine Learning (ML) models can significantly enhance the quality assurance of the food and safety through real-time monitoring, intelligent analysis, and automated decision-making.[26][27]

3.2 Equipment Downtime and Maintenance

Real-time decision-making is one of the key requirements of smart food manufacturing. As, the systems continuously generate large amount of production data which require immediate analysis and response. Accurate decision-making is essential for maintaining the quality of the product, ensuring operational efficiency, and responding effectively to different manufacturing conditions. However, achieving a real-time intelligent decision-making remains a significant challenge in many existing food manufacturing systems.

Most conventional manufacturing systems still depend on human involvement for the maintenance of the systems. Although these technologies such as Artificial Intelligence (AI), Cyber-Physical Systems (CPS), and the Industrial Internet of Things (IIoT) are increasingly being adopted, they are often being implemented as an independent system, resulting in delayed data processing, limited intelligent automation, and slow responses to changing production conditions.[1][17]

The absence of an integrated real-time decision-making mechanism can eventually lead to production delays, inefficient resource utilization, increased operational costs, inconsistent product quality, and reduced manufacturing efficiency. Furthermore, these delayed responses to the equipment failures may create a negative impact on the production continuity and customer satisfaction. Therefore, there is a need for an integrated intelligent manufacturing system which us capable of real-time data analysis, automated decision-making, and autonomous process control. The integration of the Industry4.0 technologies can enable a faster and a more accurate operational decisions, thereby improving the manufacturing efficiency, production reliability, and overall system performance.

3.3 Data Integration and the Interoperability

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3.4 Resource Utilization and Sustainability

Efficient resource utilization and sustainability have become major priorities in modern food manufacturing due to the increasing demand for environmentally friendly and cost-effective production processes. Food manufacturing industries are expected to optimize the utilization of raw materials, energy, water, and other production resources while minimizing the waste and environmental impact Achieving the sustainable manufacturing has therefore become a significant challenge for the industry [3][25].

Many conventional manufacturing systems still experience an inefficient resource utilization because of the manual operations, production inefficiencies, lack of continuous monitoring and limited processing of the data. These challenges can often lead to excessive energy consumption, unnecessary material wastage, increased production costs, and reduced operational efficiency.[30]. Poor resource management not only affects the financial management of manufacturing industries but also contributes to the environmental pollution. The inefficient utilization of these manufacturing resources indirectly reduces the overall productivity and limits the ability of these industries to achieve a sustainable production goal.

Therefore, there is a need to integrate all the Industry4.0 technologies which includes the Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), and Machine Learning (ML) for optimal resource utilization and support a sustainable manufacturing practice. The integration of all these technologies enables an intelligent resource management, reduces operational waste, improves energy efficiency, and enhances the overall sustainability of smart food manufacturing systems.

4. Proposed Methodology

4.1 Artificial Intelligence in Food Manufacturing

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of Industry 4.0, by enabling an intelligent automation, and data-driven decision-making, and process optimization in smart food manufacturing. Artificial Intelligence can be defined as a technology which enables the machines to perform tasks requiring human intelligence, including the predictive analysis, intelligent decision-making, and process optimization. As AI is one of the rapidly evolving technologies, it has gained a significant importance in modern food manufacturing due to its ability to improve operational efficiency and support the intelligent manufacturing processes. Artificial Intelligence offers numerous applications in the field of food manufacturing, including which includes quality inspection, predictive maintenance, autonomous system operation, defect detection, and production optimization. By analysing the large amount of manufacturing data, AI enables industries to identify these abnormalities, improve the production efficiency, and support timely decision-making. These capabilities have made AI an essential technology for developing an intelligent and a reliable food manufacturing system [3].

The adoption of Artificial Intelligence provides several advantages, such as improved accuracy, reduced human intervention, faster decision-making, increased productivity, and enhanced food quality. Consequently, AI forms the foundation of the intelligent manufacturing by which enables the industries to automate the complex processes while by improving the operational efficiency and the manufacturing reliability.[17]

However, the effectiveness of Artificial Intelligence is further enhanced through the Machine Learning techniques models, which enable a predictive maintenance, pattern recognition, and continuous learning from manufacturing data. The role of Machine Learning in predictive is discussed in the following section maintenance

4.2 Machine Learning for Predictive Maintenance

Machine Learning (ML) is one of the key branches of Artificial Intelligence that enables the manufacturing systems to learn from past data and real-time data without being repeatedly programmed for each and every task. In Smart Food Manufacturing, Machine Learning models plays a significant role in analysing the production data, identifying hidden patterns, and supporting intelligent decision-making. Its ability to continuously improve the prediction accuracy makes it an essential technology for developing a reliable manufacturing system. [16][17]

One of the major applications of Machine Learning in food manufacturing industry is predictive maintenance. Instead of waiting for the equipment to fail, the Machine Learning algorithms analyse the data collected from IIoT sensors, such as temperature, humidity, pressure, vibration, and equipment operating conditions, to identify abnormal patterns which may indicate a potential failure. This allows maintenance of such activities to be scheduled before the equipment breakdown occurs, therefore, reducing the unexpected downtime and improving the production continuity. Several Machine Learning algorithms are widely used for predictive maintenance in smart manufacturing systems. Some of them are Decision Tree, Random Forest, and Support Vector Machine (SVM) are commonly used to classify equipment conditions, recognize the fault patterns, predict equipment failures, and support maintenance of the systems. These algorithms improve prediction accuracy by learning from previously collected manufacturing data and continuously enhancing their performance [16][22].

The implementation of Machine Learning provides several advantages, including reduced equipment downtime, lower maintenance costs, increased equipment reliability and enhanced productivity. By identifying the potential failures at an early stage, Machine Learning enables the manufacturers to perform early maintenance, extend the equipment lifespan, and ensure the uninterrupted production processes.[29]. Although Machine Learning significantly improves predictive maintenance, intelligent manufacturing also requires continuous analysis of real-time data. Predictive Analytics and Real-Time Monitoring can further enhance the manufacturing performance by providing immediate attention into production conditions and support the operational decisions. These concepts are discussed in the following section.

4.3 Predictive Analytics and Real-Time Monitoring

Predictive Analytics and Real-Time Monitoring have become essential technologies in smart food manufacturing, which enables the industries to continuously monitor production processes, analyse the operational data, and predict potential issues before they occur. These technologies play a vital role in improving the efficiency and reliability of the smart food manufacturing systems by supporting the accurate analysis, intelligent decision-making, and continuous process monitoring. Predictive Analytics provides a meaningful insight from the collected data to support intelligent predictions, while Real-Time Monitoring enables a continuous manufacturing operation and facilitates responses to changing the production conditions.[17]

The workflow begins with the collection of real-time data from the manufacturing environment through interconnected sensors. The collected data is then transmitted to the processing system, where Predictive Analytics techniques are applied to analyse the operational information. Simultaneously, Artificial Intelligence (AI) and Machine Learning (ML) models observe the processed data, identify the patterns, generate predictions, and produce appropriate decisions based upon the manufacturing conditions. This process enables the early identification of equipment failures allowing specific actions to be taken before failures occur.[13][16]

The major applications of Predictive Analytics and Real-Time Monitoring include the equipment health monitoring, food quality inspection, predictive maintenance, automated decision-making, and system fault prediction. These applications help in maintaining the system reliability, improving the production consistency, and ensuring the delivery of high-quality food products.

The implementation of Predictive Analytics and Real-Time Monitoring offers several advantages, which includes faster response times, improved food quality, increased productivity, enhanced operational efficiency, and better resource utilization. While Predictive Analytics provides valuable insights to manufacturing operations, decision-making requires the intelligent systems to be capable of identifying these issues and selecting appropriate actions. This capability is achieved through Decision Intelligence, which is discussed in the following section.

4.4 Decision Intelligence for Smart Manufacturing

Decision Intelligence has emerged as an advanced technology that combines the Artificial Intelligence (AI), Machine Learning (ML) and data analytics to provide an automated decision-making in smart manufacturing systems. Unlike traditional decision-making methods which heavily rely on human intervention, Decision Intelligence enables manufacturing systems to analyse the operational data, and select the most appropriate course of action depending upon the current manufacturing conditions. This helps the system to improves the efficiency, reliability, and adaptability of smart food manufacturing systems.[22]

In smart food manufacturing, Decision Intelligence receives the processed information from various technologies, including Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), Artificial Intelligence, and Machine Learning. The system then analyses the conditions, equipment status, environmental parameters, and quality inspection results before determining the most suitable decision for the system. Therefore, the appropriate instructions are communicated to the manufacturing system to optimize the production processes and improve the overall operational performance.[17][22]. Decision Intelligence has numerous applications in smart food manufacturing that includes production planning, quality control, predictive maintenance planning, resource allocation, and autonomous manufacturing operations. By continuously evaluating the production data and operational conditions, the system supports intelligent decisions which improves manufacturing consistency while reducing operational risks. The implementation of Decision Intelligence offers several advantages, which includes improved decision accuracy, reduced human intervention, faster operational responses, enhanced productivity, optimized resource utilization, and increased manufacturing efficiency. These enable the industries to make a reliable decision while maintaining high production standards and improving overall system performance.

The intelligent decisions generated through Decision Intelligence can be automatically executed using the autonomous control systems, by enabling fully automated smart food manufacturing system. The role of autonomous control in intelligent manufacturing is discussed in the following section.

4.5 Autonomous Systems and Intelligent Automation

Autonomous Systems have become an important component of smart manufacturing system by enabling manufacturing processes to operate with minimal human intervention while maintaining the high levels of accuracy, efficiency, and reliability. In smart food manufacturing, autonomous systems integrate Artificial Intelligence (AI), Machine Learning (ML), Cyber-Physical Systems (CPS), and the Industrial Internet of Things (IIoT) to perform all the intelligent operation depending upon the real-time production data. This integration allows the manufacturing systems to respond automatically by changing the production conditions and improve the overall operational performance.[17]

The working of an autonomous system begins with the continuous collection of real-time data from IIoT sensors given throughout the manufacturing environment. The collected data is processed and analysed using the Artificial Intelligence and Machine Learning models to identify patterns, detect defects, and generate intelligent predictions. Based upon these predictions, the Decision Intelligence module selects the most appropriate operational action, which is then automatically executed through the actuators and manufacturing equipment without requiring continuous human supervision. Autonomous systems have a wide range of applications in smart food manufacturing system, which includes automated production control, intelligent quality inspection, predictive maintenance, a resource management, and autonomous equipment operation. These capabilities enable industries to maintain a consistent production quality while reducing the operational complexity and improving manufacturing efficiency.The implementation of autonomous systems offers several advantages, including reduced human intervention, improved operational accuracy, faster response, enhanced productivity, optimized resource utilization, and increased system reliability. The autonomous manufacturing systems support sustainable production by minimizing operational waste, reducing equipment downtime, and improving energy efficiency.[17][25]

The integration of Artificial Intelligence, Machine Learning, Cyber-Physical Systems, the Industrial Internet of Things, Decision Intelligence, and Autonomous Systems provide a technological foundation for developing an intelligent smart food manufacturing systems. Building upon all of these technologies, the next section presents the proposed AI-driven Cyber-Physical System framework for smart food manufacture.

4.6 AI-Driven CPS Framework

4.6.1 framework overview

To address the limitations which are identified in existing smart food manufacturing systems, this paper proposes an AI-driven Cyber-Physical System (CPS) framework which integrates multiple Industry 4.0 technologies into a unified intelligent architecture. The proposed framework eventually combines all the major Industry4.0 technologies, which includes the Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), Machine Learning (ML), Edge–Cloud Computing, Decision Intelligence, and Autonomous Control, to develop a complete and intelligent smart food manufacturing system.[10]

The system provides an end-to-end manufacturing workflow, from the collection of real-time data from various IIoT sensors, which later continues through the data processing, intelligent analysis, decision-making, and autonomous control. By integrating all these technologies into a unified system, the framework reduces the human intervention while improving the operational efficiency, predictive maintenance, production reliability, and food quality.[3][17]. Overall, the proposed AI-driven Cyber-Physical System framework provides an intelligent manufacturing environment which are capable of supporting real-time monitoring, automated decision-making, and sustainable food manufacturing, thereby addressing several limitations which are observed in existing smart manufacturing systems.

4.6.2 Data Acquisition using IIoT Sensors

The proposed framework begins with the data acquisition layer, where the Industrial Internet of Things (IIoT) sensors continuously collect the real-time information from the food manufacturing systems. Data acquisition refers to the process of collecting real-time operational and environmental data from the physical manufacturing system, later transferring the data for further processing. Various sensors such as temperature, humidity, pressure, and vibration sensors, are transferred throughout the manufacturing environment to continuously monitor production conditions [8]. These sensors provide accurate and real-time data which forms the foundation for the intelligent analysis and decision-making.

4.6.3 Edge–Cloud Computing Infrastructure

After data acquisition, the collected information is then transmitted to the Edge–Cloud Computing system for efficient processing, storage, and analysis. The Edge Computing layer performs an immediate processing of the data near the manufacturing environment, which reduces the communication latency and improving the system response time. The Cloud Computing layer stores the previous manufacturing data and performs a large-scale data processing and analysis. After preprocessing, the processed data is then forwarded to the Artificial Intelligence and Machine Learning models for predictive analysis and intelligent decision-making.[13][22]

4.6.4 AI Analytics Engine

The Artificial Intelligence Analytics Engine serves as the intelligence layer of the proposed framework by analysing the processed manufacturing data. The processed data which is received from the Edge–Cloud infrastructure is analysed using Artificial Intelligence and Machine Learning models. Machine Learning algorithms such as Decision Tree, Random Forest, and Support Vector Machine (SVM) identify all the hidden patterns, and generate predictive analysed data. These analytical results support quality inspection, fault detection, predictive maintenance, and intelligent manufacturing operations.[5][6]

4.6.5 Decision Intelligence Module

The Decision Intelligence Module acts as the central decision-making component of the proposed framework by evaluating the analytical results generated by the AI Analytics Engine, by selecting the most appropriate action. Based on the predictions produced by the Artificial Intelligence and Machine Learning models, the Decision Intelligence Module determines the most suitable decision for the current manufacturing condition. The selected decision is then transmitted to the autonomous control layer for execution, ensuring accurate, timely, and intelligent manufacturing operations [17], [25].

4.6.6 Autonomous Control and Actuation

The Autonomous Control and Actuation layer executes the decisions which has been generated by the Decision Intelligence Module which doesn’t requiring continuous human intervention. Based upon the selected operational decision, the control system automatically operates the manufacturing equipment, actuators and other production components. Following execution, the manufacturing environment is then continuously monitored through IIoT sensors, creating a closed-loop feedback mechanism. This continuous feedback enables to monitor the system performance, detect new operational changes, and initiate the next cycle of intelligent monitoring and decision-making.

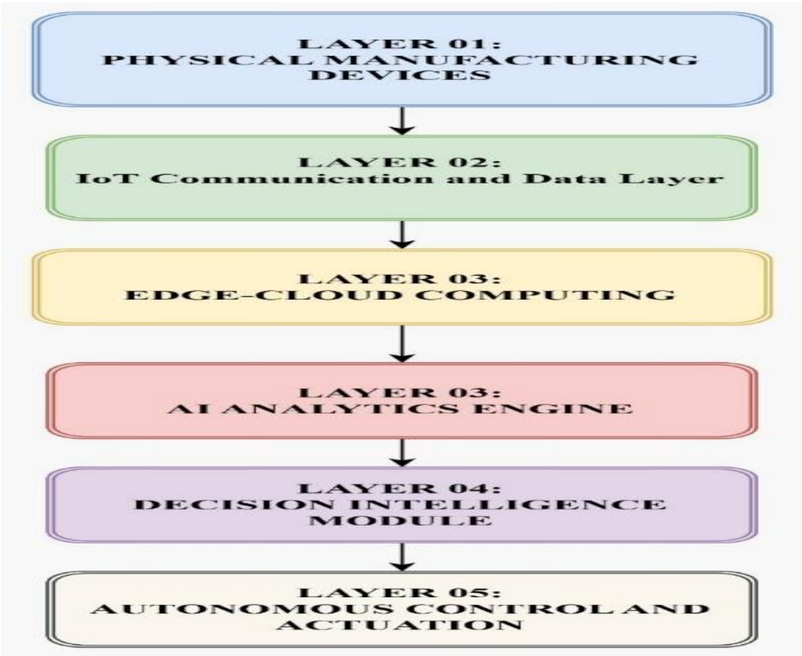

Fig. 2. The Proposed Framework Overview

End-To-End Workflow:

Step 1: Data Acquisition using IIoT Sensors

The workflow begins with the usage of IIoT sensors, which includes sensors such as temperature, humidity, pressure, and vibration sensors, throughout the food manufacturing environment. These sensors continuously collect the real-time environmental data which is required for intelligent manufacturing

Step 2: Data Transmission

The collected sensor data is then transmitted to the communication technologies such as Wi-Fi, MQTT, Bluetooth, or LoRaWAN to the Edge–Cloud Computing infrastructure for further processing.

Step 3: Edge–Cloud Data Processing

The Edge Computing layer processes the information locally to reduce the communication latency, while the Cloud Computing layer stores previous manufacturing data and performs a large-scale data processing and analysis. The processed data is then forwarded to the Artificial Intelligence Analytics Engine.

Step 4: AI and Machine Learning Analysis

The Artificial Intelligence Analytics Engine applies Machine Learning algorithms such as Decision Tree, Random Forest, and Support Vector Machine (SVM) to analyse the processed data, identify the hidden patterns, detect the defects, and generate predictive analytics for quality inspection and predictive maintenance.

Step5: Decision-Making

The analytical results generated by the AI Analytics Engine are then transferred to the Decision Intelligence Module. The module evaluates multiple operational alternatives and selects the most appropriate decision based on the current manufacturing conditions, production requirements, and system status.

Step6: Autonomous Control and Actuation

The appropriately selected decision is then transmitted to the Autonomous Control and Actuation layer, which involves the manufacturing equipment, robots, valves, and other actuators which automatically perform the required operational tasks without the involvement of human intervention.

Step 7: Continuous Feedback Mechanism

This step involves the execution of the selected action, IIoT sensors continuously monitor the updated manufacturing environment and collect new operational data. This feedback is transmitted back to the Edge–Cloud Computing infrastructure, forming a closed-loop intelligent system that continuously improves the monitoring accuracy, predictive performance, decision-making, and overall manufacturing efficiency.

The proposed end-to-end workflow enables a seamless integration of IIoT, Edge–Cloud Computing, Artificial Intelligence, Machine Learning, Decision Intelligence, and Autonomous Control into a unified intelligent manufacturing system. By supporting the continuous monitoring, predictive maintenance, automated decision-making, and closed-loop feedback, the framework provides an efficient, reliable, and a sustainable solution for next-generation smart food manufacturing systems.

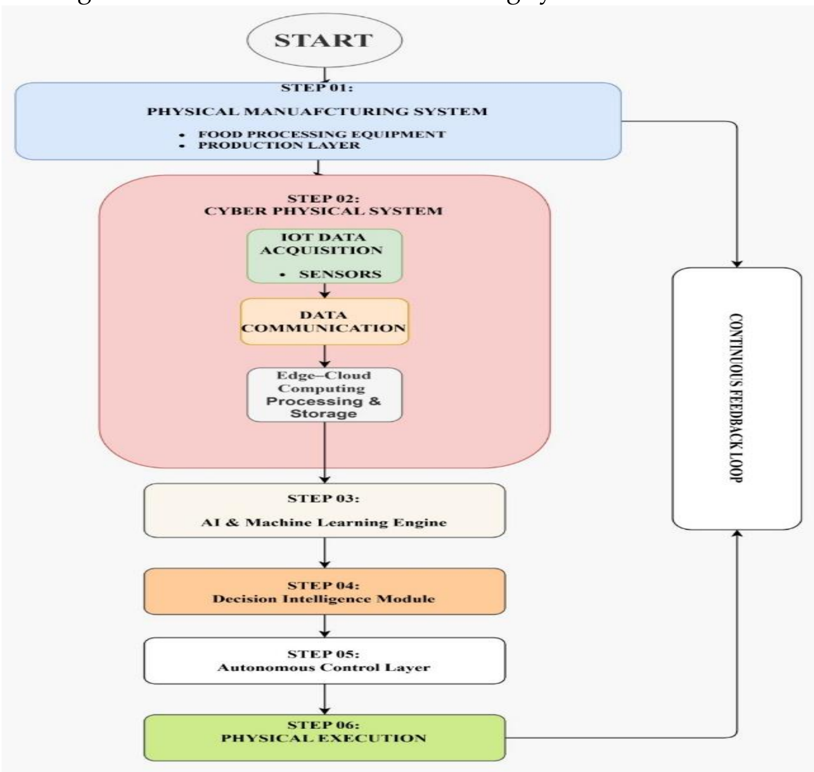

Fig. 3. The Systematic Workflow of the System

5. Industrial Applications

The proposed AI-driven Cyber-Physical System (CPS) framework has the potential to be applied across various sectors of the food manufacturing industry. By integrating the Artificial Intelligence (AI), Machine Learning (ML), the Industrial Internet of Things (IIoT), Edge–Cloud Computing, Decision Intelligence, and Autonomous Control into a unified architecture, this system supports the intelligent, data-driven, and automated manufacturing operations [7][22]. One of the major applications of the proposed framework is in food quality assurance, where real-time sensor data and AI-based analysis, which can continuously monitor product quality and detect defects in the system during production. The system can also be utilized for predictive maintenance by analysing the equipment conditions and identifying all the potential failures before they occur, thereby reducing the unexpected downtime and maintenance costs [16]

In addition, the framework can support the production process optimization through intelligent resource allocation, automated production planning, and real-time operational monitoring. Continuous monitoring of the environmental conditions such as temperature, humidity, and pressure enables the manufacturers to maintain an optimal processing conditions while minimizing material waste and improving production efficiency.

The proposed framework can further contribute to sustainable food manufacturing by optimizing the energy consumption, reducing operational waste, improving equipment utilization, and reducing unnecessary human intervention. These capabilities make the framework a suitable for Smart Food Manufacturing industries, to improve productivity, food safety and long-term sustainability.[30]

6. Future Scope

Although the proposed AI-driven Cyber-Physical System framework presents an integrated approach for the smart food manufacturing systems. Future work may focus on validating the proposed framework through real-world industrial implementation and evaluating its performance under different manufacturing environments. Such validation would also provide effectiveness, scalability, and reliability of the framework.

The framework can also be extended by incorporating the Digital Twin technology to create a virtual representation of the manufacturing processes for simulation and performance optimization. In addition, Blockchain technology can be integrated to improve food traceability, transparency, and supply chain security, while the advanced Artificial Intelligence techniques may enhance the transparency and interpretability of intelligent decision-making [26][27]. Future research may include the further investigation for the use of deep learning algorithms and reinforcement learning to improve prediction accuracy and enable adaptive learning across distributed manufacturing environments. The integration of renewable energy management and carbon-aware manufacturing strategies may also contribute to more sustainable and environmentally responsible food production systems.

Overall, the proposed framework provides a strong foundation for the development of the next-generation autonomous food manufacturing systems and offers a several opportunities for the further technological advancements as Industry 5.0 and intelligent manufacturing continue to evolve [25][30].

7. Conclusion

The rapid advancement of the Industry4.0 technologies has transformed the food manufacturing industry by enabling an intelligent automation, real-time monitoring, predictive maintenance, and data-driven decision-making. The technologies which involve Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), Machine Learning (ML), Edge–Cloud Computing, Decision Intelligence, and Autonomous Control can eventually help in improving the manufacturing performance. However, the existing approaches often implement these technologies independently, limiting the overall efficiency and intelligence of manufacturing systems.[10][17]. This paper presented an integrated AI-driven Cyber-Physical System framework that combines all these technologies into a unified architecture for smart food manufacturing. The proposed framework enables a continuous data acquisition, intelligent analysis, predictive maintenance, an automated decision-making, and autonomous control through an end-to-end workflow. By integrating sensing, computation, intelligence, and actuation into a single framework, the proposed approach addresses several limitations identified in existing systems and supports more efficient, reliable, and sustainable manufacturing operations.[30]. The proposed framework has the potential to improve the food quality, reduce the equipment downtime, optimize resource utilization, and enhance the overall manufacturing productivity while reducing the human intervention. Although the framework is conceptual and requires practical industrial validation, it still provides a comprehensive foundation for developing intelligent, autonomous, and sustainable smart food manufacturing systems. It is expected that the ideas presented in this paper will contribute to future research and industrial adoption of integrated AI-driven manufacturing solutions

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