IoT-Based Smart Monitoring and Forecasting for Pallet Production: A Review

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Abstract– **Modern manufacturing systems increasingly rely on Internet of Things (IoT) technologies to enable real-time monitoring and intelligent decision-making. IoT-based systems generate large volumes of time-series data from industrial processes, which can be leveraged for predictive analytics. However, most existing manufacturing systems still rely on static or historical estimation methods for production planning, leading to inefficiencies and suboptimal resource utilization. This paper presents a review of IoT-based monitoring systems and time-series forecasting techniques used in pallet production environments. The reviewed studies utilize real-time sensor data combined with forecasting models such as ARIMA and Long Short-Term Memory (LSTM) networks to predict short-term production output. The survey's framework also introduces a pallet ranking mechanism for prioritizing production based on demand and operational conditions. The reviewed literature indicates that integrating IoT monitoring with advanced forecasting models can improve prediction accuracy, optimize production planning, and support data-driven decision-making. This review identifies the need for unified IoT-driven monitoring and forecasting frameworks in smart manufacturing system.**

Keywords– **IoT, Time-Series Forecasting, LSTM, ARIMA, Industry 4.0 and Pallet Production**

I. INTRODUCTION

THE rapid advancement of Industry 4.0 has led to the widespread adoption of IoT technologies in manufacturing systems, enabling real-time monitoring and automation of industrial processes [1], [2]. IoT systems generate massive volumes of time-series data from sensors and machines, which require efficient storage, processing, and analysis techniques to extract meaningful insights [3], [4].

Time-series forecasting plays a critical role in industrial production systems, allowing organizations to predict future output and optimize operations [5]. Traditional forecasting methods such as ARIMA and exponential smoothing are widely used due to their simplicity, but they are limited in capturing nonlinear patterns present in industrial data [5], [6].

Recent advancements in machine learning and deep learning, including LSTM, GRU, and Transformer models, have significantly improved forecasting accuracy in time-series applications. These models are particularly effective in handling complex temporal dependencies and large-scale IoT datasets [9].

In manufacturing environments, IoT-based systems are primarily used for monitoring and predictive maintenance [11]. Similarly, smart warehouse systems utilize IoT and machine vision technologies for pallet tracking and inventory management [12]. However, most existing research focuses either on monitoring or forecasting independently, with limited integration of both functionalities.

Existing studies reveal limited integration between IoT-based monitoring and forecasting systems in pallet production environments. Therefore, there is a growing need to analyse and compare existing IoT-driven monitoring frameworks, predictive maintenance systems, and time-series forecasting techniques used in smart manufacturing applications. This review paper aims to examine recent advancements in IoT-enabled monitoring and forecasting systems, identify current research gaps, and highlight future research directions for intelligent pallet production environments.

II. COMMON IOT ARCHITECTURE LAYERS IN SMART MANUFACTURING

IoT-based industrial systems [14] commonly utilize layered architectures to support efficient data collection, communication, processing, and intelligent decision-making in smart manufacturing environments [15]. These architectures enable real-time monitoring, scalability, and interoperability among industrial devices and applications.

A) Perception Layer

Sensors collect real-time data such as: Machine performance, Pallet production count, Equipment status

B) Network Layer

Ensures communication using: MQTT, Wi-Fi / 5G, Industrial protocols

C) Processing Layer

Includes: Edge computing (low latency), Cloud computing (large-scale processing)

D) Application Layer

Implements:

- Dashboards
- Forecasting models (LSTM, ARIMA)

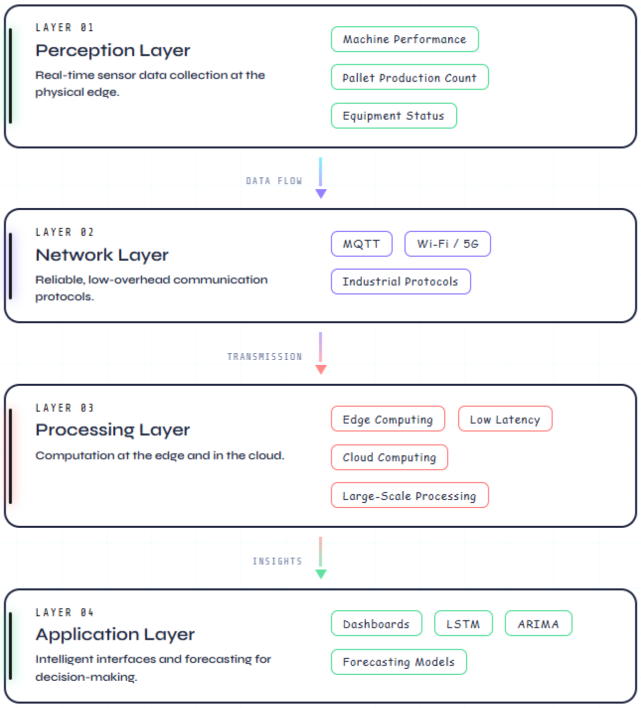

Fig. 1: IoT Layered Architecture

This layered structure enables scalable and intelligent manufacturing systems [16].

III. TIME-SERIES FORECASTING MODEL

Time-series forecasting plays an important role in Industrial IoT systems by enabling prediction of future production trends, equipment conditions, and operational behavior using historical sensor data. Forecasting models are widely applied in smart manufacturing environments to improve production planning, predictive maintenance, and resource optimization [6].

Traditional statistical approaches such as ARIMA are commonly used for short-term forecasting and stationary industrial datasets due to their simplicity and interpretability. However, these methods often struggle to capture nonlinear and complex temporal relationships present in Industrial IoT data.

Recent studies have increasingly focused on deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, for industrial forecasting applications [9]. LSTM models are capable of learning long-term temporal dependencies through memory-cell mechanisms consisting of input, forget, and output gates. These capabilities make LSTM models highly effective for analyzing sequential and nonlinear industrial sensor data [10].

The reviewed literature further highlights that deep learning-based forecasting methods generally outperform traditional statistical models in handling large-scale and continuously streaming IoT datasets.

IV. LSTM MEMORY CELL-GATE OPERATIONS

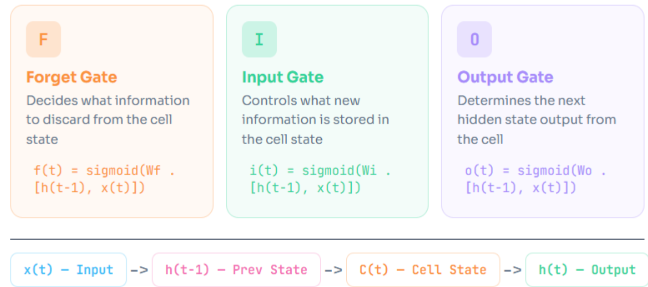

Fig. 2(a): LSTM Memory Cell Gate Operations

In addition to these traditional and deep learning models, the study [26] introduces a predictive analytics framework for IoT sensor data that integrates both classical time-series techniques and advanced deep learning architectures such as CNN-LSTM [18] hybrid models shown in Fig. 2(b). The framework is designed for industrial sensor environments where data is noisy, high-dimensional, and continuously streaming. It emphasizes feature extraction from raw sensor signals, followed by sequential learning to improve forecasting accuracy.

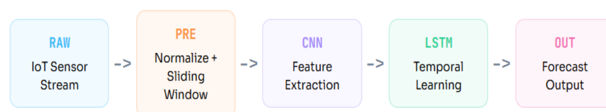

Fig. 2(b): CNN-LSTM Hybrid Pipeline - IoT Sensor Data

Furthermore, the paper highlights the importance of data preprocessing, normalization, and sliding window-based segmentation for improving model stability in real-world IoT deployments. It also demonstrates that hybrid deep learning models (CNN-LSTM) [18] outperform standalone ARIMA [8] and basic LSTM [6] models in terms of prediction accuracy and robustness under dynamic industrial conditions.

V. COMPARATIVE PERFORMANCE OF FORECASTING MODELS

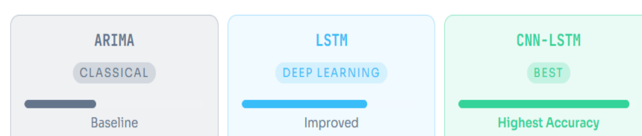

Fig. 3: Model Performance Comparison

Various studies have compared the performance of traditional statistical models and deep learning architectures for Industrial IoT forecasting applications. The reviewed literature suggests that ARIMA models perform effectively on linear and stationary datasets, while deep learning approaches such as LSTM and hybrid CNN-LSTM models provide better performance for nonlinear and multivariate industrial data [4], [18], [25].

Hybrid deep learning models, particularly CNN-LSTM architectures, demonstrated improved forecasting accuracy, robustness, and featured learning capabilities across multiple industrial case studies. These models are considered highly suitable for IoT-enabled predictive analytics systems where real-time monitoring, anomaly detection, and production forecasting are essential for intelligent decision-making in smart manufacturing environments [17].

VI. LITERATURE REVIEW

IoT-based systems are widely used for real-time monitoring of manufacturing processes and are reported to improve visibility and operational efficiency in industrial environments [3], [11]. Edge-to-cloud architecture further enhances scalability and data processing capabilities in industrial IoT systems [16].

In parallel, forecasting techniques have evolved significantly. Traditional models such as ARIMA and exponential smoothing provide baseline performance but are limited in handling nonlinear industrial data [6]. Machine learning models improve prediction but require feature engineering.

Deep learning approaches, including LSTM, GRU, and Transformer-based models, have demonstrated superior performance in forecasting industrial time-series data [7], [8]. Hybrid models combining statistical and deep learning methods have further improved accuracy and robustness [18].

IoT-based predictive maintenance systems utilize machine learning to reduce downtime and improve reliability [11]. Smart warehouse systems employ IoT and computer vision for pallet tracking and monitoring [12]. However, most of these systems focus only on monitoring or maintenance rather than production forecasting.

Recent studies further extend these capabilities but still reveal important limitations. A 2025–2026 study on strategic forecasting of IoT technologies [20] applies patent social network analysis, clustering techniques, and S-curve lifecycle modeling to identify future innovation trends. The study discovers nine major IoT technology clusters and five innovation communities, with most technologies expected to mature by 2027. While this provides strong strategic insights for policymakers and businesses, it primarily relies on patent datasets, which may not fully capture real-time industrial changes and operational data [7], [17].

Similarly, predictive maintenance using Industrial Internet of Things (IIoT) and machine learning has shown promising surveys in Industry 4.0 environments. A wastewater treatment case study demonstrates that regression-based models using real-time sensor data can effectively predict failures and estimate remaining useful life, significantly improving system reliability and reducing downtime [21].

More advanced approaches utilize transformer-based deep learning models combined with identity resolution techniques for IIoT systems. These models have reported high prediction accuracy (up to approximately 99%) in specific IIoT applications. Despite their strong performance, such methods mainly focus on equipment-level forecasting and do not address production-level demand or output prediction [22].

In smart manufacturing, edge computing and AI are increasingly used for real-time monitoring. An automated pallet racking inspection system based on MobileNetV2 demonstrates how deep learning models deployed on edge platforms can detect structural faults efficiently with low latency. This improves safety and operational efficiency; however, the system is limited to inspection tasks and does not incorporate forecasting mechanisms [23].

Despite these advancements, edge-to-cloud IIoT architectures enable scalable condition monitoring by integrating smart sensors with distributed computing systems. These architectures ensure continuous data collection and processing across manufacturing environments, enhancing system responsiveness and reliability. Nevertheless, they remain focused on monitoring rather than predictive production analytics [24].

The Smart Warehouse 4.0 system integrates IoT sensors with machine vision to automate pallet tracking and handling. The system improves warehouse efficiency, reduces human errors, and provides real-time visibility of pallet movement. However, similar to other studies, it does not address forecasting of pallet production or demand, which is critical for planning and optimization [25].

A critical research gap exists in integrating real-time IoT monitoring with forecasting models specifically for pallet production systems. This review highlights this gap and discusses the need for unified IoT-driven monitoring and forecasting approaches in future research.

The detailed review of literature and comparison analysis has been shown in Table I below.

Ref	Authors	Title	Year	Problem Statement	Methodology	Techniques	Dataset	Tools	Key Findings/Results	Limitations/ Research Gaps	Proposed Work
[19]	Maghsoudi, Mehrdad; Nourbakhsh, Reza; Kermani, Mehrdad Agha Mohammad Ali; Khanizad, Rahim;	Strategic forecasting of internet of things technologies through patent social network and innovation cluster analysis	2025	Lack of unified forecasting framework for IoT evolution	Patent analytics	BERT, K-means, S-curve, Louvain clustering	154,227 IoT patents	Python, NLP tools	9 IoT clusters and 5 collaboration networks	High computational cost	Apply ML forecasting on industrial IoT data
[26]	Abd Elhaleem, Sameh; Zanfal, Abdallah; Hamdy, Mohamed;	Predictive maintenance based on IIoT and machine learning aligned with industry 4.0: a case study in waste-water treatment plant	2025	Unexpected industrial failures and downtime	Case study + regression modeling	ML regression, IoT sensor fusion	Industrial sensor data (PLC)	Node-RED, Python	Accurate RUL prediction and fault detection	Limited scalability	Improve multi-machine predictive system
[27]	Farahani, Mojtaba A; El Kalach, Fadi; Harper, Austin; McCormick, MR; Harik, Ramy; Wuest, Thorsten;	Time-series forecasting in smart manufacturing systems: An experimental evaluation of the state-of-the-art algorithms	2025	Lack of benchmark evaluation of TSF models	Experimental comparative study	ARIMA, LSTM, Transformer	13 manufacturing datasets	Python ML libraries	MLP and PatchTST best performance	No hyperparameter tuning	Hybrid optimized LSTM model
[28]	Hossan, Md Zikar; Sultana, Taslima;	AI for Predictive Maintenance in Smart Manufacturing	2025	High downtime and maintenance cost	Systematic review	ML, DL, Data Analytics	Literature-based	Python, ML tools	AI improves maintenance efficiency	Data sparsity, explainability issues	Explainable IoT-LSTM model
[21]	Qi, Zhibo; Du, Lei; Huo, Ru; Huang, Tao;	Predictive maintenance based on identity resolution and transformers in IIoT	2024	High false alarms in traditional PdM	Transformer-based framework	Transformer, sequence modeling	Industrial IoT sensor streams	Deep learning frameworks	99% accuracy, low MAE	Complex deployment	Lightweight IoT transformer model
[43]	Elkateb, Sherien; Métwalli, Ahmed; Shendy, Abdelrahman; Abu-Elanien, Ahmed EB;	Machine learning and IoT Based predictive maintenance approach for industrial applications	2024	Machine failures causing production loss	Supervised ML classification	AdaBoost classifier	Knitting machine dataset	Python, Scikit-learn	92% accuracy in fault classification	Limited to textile domain	Cross-industry generalization model
[44]	Joha, Md Ibne; Rahman, Md Minhazur; Nazim, Md Shahriar; Jang, Yeong Min;	A secure IIoT environment that integrates AI-driven real-time short-term active and	2024	Need for secure real-time industrial monitoring	Deep learning + anomaly detection	TCN-GRU-Attention, Isolation Forest	Energy consumption	Edge + cloud systems	High accuracy forecasting & anomaly detection	Edge resource constraints	Lightweight edge AI model

		reactive load forecasting with anomaly detection: a real-world application									
[5]	Fatima, Syeda Sitara Wishal; Rahimi, Afshin;	A review of time-series forecasting algorithms for industrial manufacturing systems	2024	Lack of clear TSF model selection guidance	Literature review	ARIMA, SVM, ANN, GAN	Multiple industrial datasets	ML libraries	Hybrid models outperform traditional methods	No unified benchmark	Adaptive TSF selection framework
[22]	Hu, Daidi;	Automated pallet racking examination in edge platform based on MobileNetV2: Towards smart manufacturing	2024	Manual inspection inefficiency in warehouses	Edge AI vision system	YOLOv5, MobileNetV2	Warehouse images	Edge devices, Python	Real-time defect detection system	Hardware dependency	Improved low-cost IoT inspection system
[25]	Selmy, Hend A; Mohamed, Hoda K; Medhat, Walaa;	A predictive analytics framework for sensor data using time series and deep learning techniques	2024	Need for accurate IoT sensor forecasting	Comparative forecasting framework	ARIMA, SARIMA, LSTM, CNN-LSTM	IoT sensor datasets	Apache Spark, Kafka	CNN-LSTM best accuracy	Limited generalization	Multi-domain sensor forecasting model
[29]	Song, Xiaobao; Deng, Liwei; Wang, Hao; Zhang, Yaoan; He, Yuxin; Cao, Wenming;	Deep learning-based time series forecasting	2024	Inefficiency of traditional forecasting methods	Comprehensive DL survey	LSTM, Transformers, MLP	Multiple benchmarks	Python DL frameworks	DL models outperform statistical models	High computational cost	Efficient hybrid lightweight DL model
[30]	Shah, Muhammad Jasim; Saleem, Muhammad; Akhter, Muhammad; Wajid, Muhammad; Malik, Javaid Ahmad;	Deep Learning and Time Series Analysis for Internet of Things Device Predictive Maintenance	2024	IoT device failure prediction challenges	TSA + DL framework	RNN, LSTM	IoT logs + sensor data	Python, ML tools	High accuracy PdM system	Lack of explainability	XAI-based IoT maintenance model
[31]	Kumar, Vinod; Prakash, M; Thamburaj, Sam;	Deep learning-based predictive maintenance for industrial IoT applications	2024	High downtime and inefficiency in industrial systems	DL-based PdM framework	CNN, RNN, hybrid DL, transfer learning	Industrial IoT sensor data	Python, DL frameworks	Improved operational efficiency and reduced downtime	Data quality and scalability issues	Lightweight edge DL-PdM system
[32]	Kaya, Mahmut; Utku, Anıl; Canbay, Yavuz;	A hybrid CNN-LSTM model for predicting energy consumption and production across multiple energy sources	2024	Inefficient energy forecasting in smart grids	Sliding window regression model	CNN, LSTM, hybrid CNN-LSTM	EXIST Turkey energy dataset (2018–2023)	Python, ML libraries	CNN-LSTM achieved lowest RMSE & MAE	Limited external validation	Multi-region energy forecasting model

[33]	Mary, P Arockia; Sharma, Avinash; Dekka, Satish; Gowda, V Dankan; Singh, Mandeep;	Deep learning approaches for real-time data analytics in IoT sensor networks	2024	Real-time IoT data processing limitations	Deep learning architecture evaluation	1D CNN, GRU, LSTM	IoT sensor network data	Python, DL frameworks	DL outperforms traditional methods in speed & accuracy	High computational cost	Optimized real-time IoT analytics model
[34]	Aboshosha, Ashraf; Haggag, Ayman; George, Neseem; Hamad, Hisham A;	IoT-based data-driven predictive maintenance relying on fuzzy system and artificial neural networks	2023	Fault detection inefficiency in industrial machines	Fuzzy + DL-based PdM system	Fuzzy Logic System, ANN	Industrial production line data	IoT systems, AI tools	Improved fault detection and reduced human error	Limited scalability	Hybrid fuzzy-deep learning PdM system
[35]	Venkateshwari, P; Veeraiah, Vivek; Talukdar, Veera; Gupta, Deena Nath; Anand, Rohit; Gupta, Ankur;	Smart city technical planning based on time series forecasting of iot data	2023	Urban traffic congestion and planning inefficiency	ML-based forecasting system	Random Forest, Decision Tree	IoT traffic sensor data	Python ML tools	Accurate traffic prediction for smart city planning	Limited to traffic domain	Multi-domain smart city forecasting model
[1]	Kashpruk, Nataliia; Piskor-Ignatowicz, Cezary; Baranowski, Jerzy;	Time series prediction in industry 4.0: a comprehensive review and prospects for future advancements	2023	Lack of unified TS forecasting framework	Literature review	IoT, AI, Big Data analytics	Multi-source studies	Analytical review	TS forecasting improves industrial decision-making	Lack of implementation framework	Industry 4.0 forecasting system
[36]	Yakoi, Polycarp Shizawaliyi; Meng, Xiangfu; Cui, Shuolin; Suleman, Danladi; Yang, Xueyong;	Analysis of time series data generated from the internet of things using deep learning models	2023	Difficulty in analyzing large IoT datasets	DL-based data analysis framework	Deep learning models	IoT time-series datasets	Python, DL tools	DL significantly improves prediction & anomaly detection	Interpretability issues	Explainable IoT DL model
[37]	Ren, Lei; Jia, Zidi; Laili, Yuanjun; Huang, Di;	Deep learning for time-series prediction in IIoT: progress, challenges, and prospects	2023	Complexity of IIoT time-series forecasting	Survey + framework proposal	DL models (LSTM, CNN, Transformer)	IIoT datasets	Analytical models	DL enables intelligent IIoT forecasting	Scalability and generalization issues	Adaptive IIoT forecasting framework
[38]	Papastefanopoulos, Vasilis; Linardatos, Pantelis; Panagiotakopoulos, Theodor; Kotsiantis, Sotiris;	Multivariate time-series forecasting: A review of deep learning methods in internet of things applications to smart cities	2023	Complex multivariate IoT forecasting challenges	DL review	LSTM, CNN, Transformers	Smart city IoT datasets	ML frameworks	DL effective for multivariate forecasting	High computational cost	Efficient multivariate IoT model

[23]	Li, Zhi; Fei, Fei; Zhang, Guanglie;	Edge-to-cloud IIoT for condition monitoring in manufacturing systems with ubiquitous smart sensors	2022	Cloud congestion and anomaly detection issues	Edge-cloud architecture	LSTM anomaly detection	Industrial machine dataset	Edge computing, IoT systems	Reduced network load & improved anomaly detection	Limited labeled fault data	Edge AI-based PdM system
[39]	Wahid, Abdul; Breslin, John G; Intizar, Muhammad Ali;	Prediction of machine failure in industry 4.0: a hybrid CNN-LSTM framework	2022	Machine failure prediction inefficiency	Hybrid DL model	CNN-LSTM	Microsoft machine dataset	Python, ML tools	Highest prediction accuracy achieved	Complex model tuning	Optimized lightweight CNN-LSTM model
[40]	Mishra, Sambeet; Bordin, Chiara; Taharaguchi, Kota; Purkayastha, Adri;	Predictive analytics beyond time series: Predicting series of events extracted from time series data	2022	Traditional time-series models struggle with high data volume & velocity in wind energy forecasting	Event-based predictive analytics framework	Deep learning models + event extraction	6 years wind power & temperature data	Python, DL frameworks	Event-based prediction reduces data volume while maintaining accuracy	Limited generalization to other domains	Extend event-based forecasting to IoT industrial systems
[41]	Vukićević, A; Mladineo, Marko; Banduka, Nikola; Mačužić, I;	A smart Warehouse 4.0 approach for the pallet management systems using machine vision and Internet of Things (IoT): A real industrial case study	2021	Inefficient warehouse and pallet management systems	IoT + machine vision case study	Computer vision, IoT sensors	Real industrial warehouse data	IoT devices, vision systems	Improved pallet tracking and reduced inventory waste	Limited automation scalability	AI-based autonomous pallet management system
[42]	Kumar, Raghavendra; Kumar, Pardeep; Kumar, Yugal;	Time series data prediction using IoT and machine learning technique	2020	Air quality prediction inefficiency using traditional models	Machine learning forecasting approach	Linear Regression	Delhi & NCR air quality sensor data	Python ML tools	Achieved accurate AQI prediction with low error metrics	Limited to linear models	Deep learning-based environmental forecasting model

VII. REVIEW METHODOLOGY

This review paper adopts a systematic literature review approach to investigate recent advancements in IoT-based monitoring, predictive maintenance, and time-series forecasting techniques for smart manufacturing and pallet production systems. Relevant research articles were collected from major scientific databases including IEEE Xplore, Springer, ScienceDirect, MDPI, and Google Scholar.

The literature search was performed using keywords such as "Industrial IoT," "smart manufacturing," "time-series forecasting," "LSTM," "ARIMA," "predictive maintenance," "warehouse management," and "pallet production systems." The review primarily focused on studies published between 2020 and 2026, while several foundational studies published earlier were also included due to their significance in Industrial Internet of Things (IIoT) research [13], [42].

The inclusion criteria considered peer-reviewed journal and conference papers related to:

IoT-enabled industrial monitoring systems

Time-series forecasting techniques

Deep learning and hybrid forecasting models

Predictive maintenance frameworks

Smart warehouse and pallet management systems

Duplicate studies, non-English articles, and irrelevant publications were excluded during the screening process.

The selected studies were comparatively analyzed according to the following aspects:

- IoT architecture and sensor integration [14]
- Data preprocessing and time-series analytics [3]
- Forecasting approaches including ARIMA, LSTM, GRU, CNN-LSTM, and Transformer models [6], [7], [8], [17], [18], [27], [32]
- Predictive maintenance applications in IIoT environments [20], [21], [28], [31], [34]
- Smart warehouse and pallet management systems [12], [22], [24], [41]

Performance evaluation metrics and industrial applicability

Special attention was given to recent studies focusing on hybrid deep learning architectures, edge-cloud IIoT systems, and intelligent forecasting mechanisms for industrial automation and production optimization [15], [16], [25], [37].

Comparative Analysis and Discussion

The reviewed literature demonstrates that IoT-based monitoring systems significantly improve industrial visibility, operational efficiency, and real-time decision-making capabilities in smart manufacturing environments [2], [13], [23]. IoT sensors and connected devices enable continuous monitoring of production activities, machine status, energy consumption, and environmental conditions, thereby supporting predictive and intelligent industrial operations.

Several studies emphasized the importance of time-series forecasting techniques in industrial systems. Traditional statistical models such as ARIMA remain effective for stationary datasets and short-term forecasting tasks [6]. However, deep learning approaches, particularly Long Short-Term Memory (LSTM) networks, showed superior performance in capturing temporal dependencies and handling nonlinear industrial data patterns [4], [25], [27], [36].

Recent literature further highlighted that hybrid models combining CNN and LSTM architectures outperform standalone forecasting models by integrating feature extraction and sequential learning capabilities [17], [18], [32], [39]. Transformer-based forecasting methods also demonstrated promising performance in predictive maintenance and industrial anomaly detection tasks [21].

In predictive maintenance applications, IoT-enabled frameworks contributed to reducing equipment downtime, improving maintenance scheduling, and enhancing resource utilization [20], [28], [31], [34]. Edge-cloud integrated IIoT architectures were also found effective for real-time industrial analytics and scalable deployment [15], [23].

Additionally, smart warehouse and pallet management systems received considerable attention in recent studies. IoT-based pallet tracking, machine vision systems, and intelligent logistics frameworks improved warehouse efficiency, pallet inspection, and operational management [12], [22], [24], [41].

The reviewed studies collectively indicate that combining IoT infrastructure with advanced deep learning forecasting techniques can significantly improve industrial productivity, predictive accuracy, and operational sustainability.

VIII. RESEARCH GAPS AND FUTURE WORKS

Despite substantial advancements in Industrial IoT and time-series forecasting, several research challenges remain unresolved. Most existing studies focus on general smart manufacturing applications, while limited research specifically addresses floor-level pallet production optimization and intelligent pallet ranking systems.

Furthermore, many forecasting studies primarily emphasize prediction accuracy without integrating real-time decision-support mechanisms for production prioritization, scheduling optimization, and adaptive manufacturing control. Scalability challenges limited industrial datasets, and computational complexity also remain critical concerns for practical deployment in large-scale manufacturing systems [1], [11], [37].

Another important limitation identified in the literature is the lack of explainability and interpretability in deep learning forecasting models. Although hybrid architectures and transformer-based approaches achieve high predictive performance, their industrial adoption may be restricted due to limited transparency and high computational requirements [8], [21].

Future research should therefore focus on:

- Hybrid deep learning forecasting frameworks for industrial production systems
- Intelligent pallet ranking and scheduling mechanisms
- Explainable Artificial Intelligence (XAI) for industrial forecasting
- Real-time edge-cloud IIoT architectures
- Federated learning approaches for secure industrial analytics [7]
- Large-scale validation using real manufacturing datasets

- Integration of AI-driven predictive maintenance with smart logistics systems

These research directions may contribute toward the development of scalable, intelligent, and autonomous Industry 4.0 manufacturing environments.

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