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Surveying on Big Data and Predictive Analytics – Based Machine Learning for Smart Industrial IoT Applications

Harsha Vardhan Reddy Kavuluri[1]*, Akhil Kumar Pathani[2], Ajay Dasari[3], Venkata Kishore Chilakapati[4], Srikanth Reddy Keshireddy[5] and Venkata Teja Nagumotu[6]

[1]Lead Database Administrator, Wissen infotech Inc, USA

[2]Network Engineer, Ebay, USA

[3]Senior Support Engineer, Microsoft, USA

[4]Technical Advisor, Microsoft, USA

[5]Senior Software Engineer, Keen Info Tek Inc, USA

[6]Sr Network Engineer, Techno-bytes Inc, USA

ABSTRACT

The progress of Industry 4.0 has allowed building intelligent factories with the application of artificial intelligence (AI), big data, and the industrial internet of things (IIoT) to boost system intelligence, automation, and efficiency. The IIoT devices produce very large amounts of heterogeneous and high-velocity data, and scalable big data architectures and sophisticated analytics are necessary to find actionable insights. Machine learning (ML) models, including Random Forest, Support Vector Machines, and Long Short-Term Memory networks, are crucial for process optimization, problem detection, quality control, and predictive maintenance. Nevertheless, the combination of big data and IIoT brings a number of problems such as data heterogeneity, real-time processing limitations, model interpretability, security and privacy issues. This article highlights the uses and difficulties of big data-driven IIoT applications, reviews the lifecycle of big data in IIoT contexts, and discusses some of the most commonly used ML-based predictive analytics. The results highlight the potential of introducing change to IIoT in relation to ML, but also the necessity of implementing sophisticated data management, explainable AI, and secure architectures to achieve the potential of smart industrial environments.

***Corresponding author**

Harsha Vardhan Reddy Kavuluri, Lead Database Administrator, Wissen infotech Inc, USA.

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Introduction

The "smart factory" of Industry 4.0 more intelligent and aware, capable of handling complicated tasks on its own. The smart factory optimizes manufacturing processes' performance, quality, controllability, and transparency by using cutting-edge technology such as the industrial internet of things (IIoT), big data, and artificial intelligence (AI) [1]. These days, it is the centre of Industry 4.0 and is of great interest to governments, businesses, and researchers.

IoT is the networking of computers and physical things that allows them to exchange and gather data. Typically, cloud platforms are used to aggregate and store the acquired data. These gadgets may be remotely sensed and monitored thanks to IoT. Automation is becoming possible in a number of sectors because to internetworking and connection. The core concept of the Industrial Internet of Things (IIoT) is the application of Internet of Things (IoT) technologies in industrial control systems (ICSs). ICSs are a crucial part of critical infrastructures and have long been used to monitor industrial machinery and activities [2]. They monitor every event that occurs in the industrial systems, gather and analyze data in real time, and monitor and communicate with devices in real time [3]. Increased network intelligence and security are achieved by integrating IoT technology into existing systems to enhance the automation and optimization of industrial processes.

Big Data demands sophisticated computer systems due to its size, complexity, and diversity. AI has made it possible for it to be done efficiently. The computers used to be programmed to do a certain task. AI has now rendered it intelligent by enabling it to precisely comprehend external data, take lessons from it, and use those lessons to do certain tasks with adaptation and flexibility [4]. Through a variety of uses, including automation, predictive quality analytics, and Artificial Intelligence (AI), the industrial production process can be revolutionized through perceptual engineering system identification. Recently, several Internet of Things applications have made active use of Deep Learning

(DL), one of the various machine learning (ML) approaches [5]. The fact that conventional ML techniques do not meet the new analytical requirements of IoT systems is the reason behind this intense attention for DL. The IoT data collecting and management hierarchy, IoT systems instead require distinct contemporary data analysis techniques and AI technologies.

Structure of Paper

The paper is organized as follows: Section II provides a big data architecture and frameworks in industrial IoT, Section III outlines ML techniques for predictive analysis in IoT, Section IV details challenges in big data–driven IIoT predictive analytics, and Section V presents a literature study. Finally, Section VI concludes the findings and recommends directions for future research.

Big Data Architecture and Frameworks in Industrial IoT

An IoT-based big data analytics platform with the right algorithms and communication channels may be built to track and describe energy behaviours in different types of buildings [6]. This section outlines the key architectural components and big data frameworks that enable high-performance IIoT analytics.

IoT Big Data

The Internet of Things (IoT) is widely recognized as one of the primary sources of big data since it relies on the Internet to link a vast number of smart devices that often transmit the condition of their surroundings. Finding and extracting significant patterns from massive amounts of raw input data is the primary goal of big data analytics, which produces better insights for forecasting trends and making decisions [7]. The general characteristics of large data have been discussed in a number of publications from many angles, including volume, velocity, and diversity. However, use the "6V's" qualities depicted in Figure 1 and the overall concept of big data to describe IoT big data:

Figure 1: 6v’s of Big Data

- **Volume:** The amount of data determines whether a dataset is classified as big data or conventional massive/very huge data. This characteristic is seen in the vastly increased amount of data collected by IoT devices.
- **Velocity:** The generation and processing rates of IoT big data are sufficiently enough to enable real-time big data availability. This explains why, given the tremendous rate of data generation, analytics need sophisticated tools and technology to function well.
- **Variety:** In general, there are many different kinds and sizes of big data. Data that is unstructured, semi-structured, or structured may be incorporated [8]. Among IoT may be a variety of data forms, such as text, audio, video, sensory data, and more.
- **Veracity:** The quality, consistency, and reliability of the data are referred to as veracity; these attributes ultimately result in precise analytics. IoT applications require extra care to maintain this quality, particularly those involving crowd-sensing data.
- **Variability:** The various data flow rates are referred to by this characteristic. Different data producing components may have irregular data flows, depending on the type of IoT application. Furthermore, depending on certain periods, a data source may have varying data load rates.
- **Value:** Value is the conversion of large data into insightful knowledge that gives businesses a competitive edge. The way that data is handled and the underlying processes or services both have a big influence on a data value.

Big Data Lifecycle in Industrial IoT

The Big Data lifecycle in Industrial Internet of Things (IIoT) surroundings characterizes the overall lifecycle of how data is created, exchanged, stored, processed, and ready to be utilized in analytics [9]. With industrial systems highly distributed over an array of sensors, actuators, programmable controllers and edge devices, data management needs to follow a structured and optimized lifecycle, in order to achieve accuracy, scalability and real-time responsiveness. This lifecycle goes through major phases as outlined below.

Data Sensing and Acquisition

The data collecting step of the IIoT Big Data life cycle is the first and most crucial stage [10]. Smart meters, heterogeneous sensors, RFID tags, PLCs, and cyber-physical systems continuously observe machine operations, environmental factors, vibration, temperature, pressure, flow of production in the industrial environment [11]. These sensors produce high velocity data streams that are an indication of the real-time health and performance of industrial assets. The current sensing systems assert adaptive sampling, multimodal data gathering and a self-calibration to guarantee reliability of the data.

Data Storage (HDFS, NoSQL, Time-Series Databases)

Considering the large amount and speed of IIoT data, storage should support both the structured and unstructured data. There are three broad categories of repositories that are usually used to store industrial data:

- **Hadoop Distributed File System (HDFS):** Applied to batch storage and distributed processing of historical data on a large scale [12]. HDFS is fault-tolerant and horizontally scalable, which is why it is the best solution to use in storing long-term logs and machine operational data.
- **NoSQL Databases (MongoDB, Cassandra, HBase):** Written to be flexible with the schema and high write throughput. NoSQL databases store semi-structured or unstructured sensor data and allow distributed queries, which is capable of near-real-time analytics.
- **Time-Series Databases (Timescale DB, OpenBSD, Influx DB):** Tuned to sequential time-indexed information produced by industrial sensors [13]. TSDBs are efficient in compression, read/write and real-time monitoring.

The three are frequently merged in a layered storage architecture to satisfy different needs of speed and scalability as well as depth of analysis.

Challenges of IoT

IoT can transform how the Internet functions, but it also presents issues that must be resolved. A few major obstacles are as follows:

- **Naming and Identity Management:** It is necessary to identify the vast number of linked devices in a distinctive and dynamic manner.
- **Interoperability and Standardization:** It is essential that devices be standardized in order for them to be interoperable.
- Information Privacy: The privacy of the data must be taken into account because it may be crucial.
- **Objects Safety and Security:** Distributed devices may sustain physical harm, which raises concerns about their security and safety.
- **Data Confidentiality and Encryption:** To prevent abuse, data must be encrypted before being transferred.

Machine Learning Techniques for Predictive Analysis In Iiot

A subfield of computer science known as without explicit programming, robots may learn thanks to machine learning (ML), a kind of artificial intelligence [14]. ML emerged from computational learning theory and pattern recognition. Here, some fundamental ideas in ML are covered, along with commonly used ML algorithms for intelligent data analysis.

Random Forest (RF)

Several decision trees are created by the popular ensemble learning model Random Forest and pools the predictions of the trees together to give greater accuracy and strength. Random Forest provides consistent and consistent results in Industrial IoT environments where sensor information is notorious due to noise, high-dimensional, and values that are likely to be missing. Random Forest is widely used in predictive maintenance, fault classification, and equipment health monitoring tasks because of its good generalization ability.

Support Vector Machine (SVM)

The popular method of supervised learning for classification, Support Vector Machines (SVM) perform well, particularly when working with limited or imbalanced data [15]. SVM is helpful in uncovering hidden patterns in machine behavior by determining the best hyperplane to maximize the distance between various categories.

Long Short-Term Memory (LSTM)

LSTM-based networks to mimic a sequence and patterns over time, recurrent neural networks (RNNs) of the LSTM network type are employed. The LSTM is better than the standard RNN because it uses memory cells to store long-term information, thus, it is the best option where running sensor data in IIoT devices is required.

Predictive Analysis Applications in IIoT

Predictive analysis is a transformational aspect of Industrial IoT (IIoT) that makes use of ML, real-time sensing, and data driven intelligence to optimize the operations of the industry [16]. Industries predict equipment failure, increase productivity, minimize downtime, and make the system more efficient through constant monitoring and advanced analytics. The subsections that follow outline the most vital areas of application of predictive analytics in IIoT-based environments.

Predictive Maintenance

Predictive maintenance is also among the commonest uses of IIoT analytics. By routinely monitoring sensor data, such as vibration, machine learning (ML) models can forecast the equipment's remaining usable life (RUL) and identify early degradation, temperature, pressure, and acoustics to determine the necessary actions to prevent harm to equipment. This allows industries to perform maintenance only when needed thereby minimizing the unplanned downtimes, costs of repair, and increasing the life of equipment.

Fault Detection and Diagnosis

Finding anomalous patterns in industrial systems and determining their underlying causes is known as fault detection and diagnosis, or FDD. The IoT sensors provide high-frequency data to the ML models, which identify variations of normal operation conditions. After detecting a fault, diagnostic algorithms categorize the nature and magnitude of the issue and assist the technicians in taking specific corrective measures.

Quality Management and Process Improvement

Predictive analytics are used in quality control and process optimization to achieve consistency of products and enhance efficiency in manufacturing processes. ML algorithms compare parameters of production, including temperature, pressure, material flow, and machine parameters, with the goal of recognizing those combinations that result in any defect or less-optimal production.

Challenges in Big Data–Driven IIoT Predictive Analytics

The significant advancements in Industrial IoT (IIoT) and the growing integration of ML and big data technologies, several challenges are discussing below:

- **Data-Related Challenges:** Heterogeneity and quality of data produced by various sensors, machines, and one of IIoT analytics' biggest difficulties is cyber-physical systems. The data used in IIoT is usually noisy, contains gaps, lacks consistency, and has different sampling rates. Moreover, the unlabeled datasets make limited usage of supervised ML models [17]. It is also hard to train correct classifiers to detect anomalies and diagnose fault because data imbalance (normal operational data is significantly greater than fault data) also complicates things.
- **Systems and Computational Problems:** The IIoT systems create vast and high-speed streams of data which demand a lot of computing power to handle real-time. Edge devices typically have small processing units, memory, and energy reserves, so it is difficult to execute complex ML models on the device [18]. To process all the data in the cloud platforms creates latency, bandwidth limitations, and network congestion. Moreover, in a dynamic industrial environment where reliability is a crucial aspect, the scalability and fault tolerance of a distributed big data infrastructure are hard to accomplish.
- **Security and Privacy Problems:** The more industrial systems are interconnected, the more they become susceptible to cyber-attacks. The secure transmission of the data, inhibiting unauthorized access, and tracing the malicious activities are also significant issues. The sensitive industrial information, including the information on operational measures, production plans, and machine states, should be secured throughout storage and communications.
- **Model-Related Challenges:** A large dimensional sensor data can lead to overfitting, which decreases the generalization strength of the model. Several ML and DL systems are deemed black boxes and thus engineers find it hard to explain the predictions; thus, there is a need to use Explainable AI (XAI) to achieve decision-making in the industrial environment.

Literature Review

This literature review presents an in-depth analysis of recent studies on Predictive Analysis in Industrial IoT. Table I offers a consolidated overview of these works, highlighting the methods, findings, challenges, and suggested directions for future research.

Al-Hawawreh and Sitnikova (2019) To precisely identify malicious activity, the latent representation of a high dimension of the acquired data may be extracted using DL techniques. In particular, a hybrid feature engineering approach that combines variational and classical auto-encoders forms the basis of the proposed model. This hybrid approach provides a clear image of the system operations that have been gathered while also reducing the dimension of the data. After that, the new feature is fed into a classifier that uses batch normalization techniques and deep neural networks. vector. The experimental results included in the paper's conclusion demonstrate that the model works better at detecting ransomware than other currently used techniques [19].

Sun, Liu and Yue (2019) provide a cloud computing and cooperative edge-based intelligent computing architecture for the IIoT. The computer architecture suggests an AI-enhanced offloading framework to optimize service accuracy. When allocating the traffic intelligently to edge servers or via a suitable means to remote cloud, it takes service accuracy into account in addition to latency. To demonstrate how the suggested framework enhances performance, a case study on transfer learning is conducted [20].

Qiu et al. (2019) suggests a ML-based spammer identification method for industrial mobile networks based on the Gaussian mixture model (SIGMM). It offers sophisticated spammer identification without depending on shaky and unstable connections. Throughout the model's construction, SIGMM incorporates data presentation, classifying each user node into a single class. Compare the SIGMM to the hybrid fuzzy c-means (FCM) clustering method and reality mining approach employing a dataset from a cloud server's mobile network. SIGMM performs better than a number of earlier systems in terms of time complexity, accuracy, and recall, according to simulation data [21].

Kavana and Neethi (2018) identify some of the most prevalent electrical issues, such as single phasing, overload, ground fault, and uneven voltage, undervoltage, and overvoltage, using a quick forward artificial neural network model. A different model-free monitoring method records only the input that the motor receives, using the motor as a sensor. In both normal and pathological conditions, a classifier sets limitations on voltage and current levels. The neural network is trained and tested using real-time data from an induction engine of 0.33 horsepower [22].

Wu and Tan (2018) A large data platform with distributed power that combines computing, mining, and storage, and analytical characteristics was developed in response to the power industry's requirement to handle and analyze vast volumes of heterogeneous data. The experimental findings demonstrate that the distributed computing system may significantly increase data processing efficiency. At the same time, can increase capacity to anticipate load by utilizing data mining technologies to evaluate home power data and determine the electric load's distribution and evolving regulations [23].

Kanawaday and Sane (2017) investigates the use of Autoregressive Integrated Moving Average (ARIMA) forecasting on time series data collected from a Slitting Machine's many sensors in order to improve production overall by anticipating possible defects and quality problems. With applications in quality monitoring and control, lowering maintenance costs, and overall enhancing the industrial process, ML therefore seems to be an essential component of IioT [24].

Jiang and Kuo (2017) Prognostics and health management (PHM) in smart factories rely on figuring out how long a machine or component will last (RUL). This study improves the convolutional neural network (CNN) DL for RUL estimation in smart industrial applications. The enhanced CNN DL is used to estimate the RUL of aero-propulsion engines utilizing the NASA C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) data set. It has been demonstrated to perform better than similar techniques [25].

Table 1: Summary of literature Overview on Predictive Analysis in Industrial IOT

Author(s)	Method	Findings	Challenges Identified	Future Strategy
Al-Hawawreh & Sitnikova (2019)	Hybrid feature engineering using Classical Autoencoder + Variational Autoencoder (VAE); Deep Neural Network classifier with Batch Normalization	Hybrid autoencoder approach extracts meaningful latent features and improves ransomware detection accuracy; Outperforms existing models	Handling extremely high-dimensional data; Need for robust generalization across diverse ransomware families	Extend hybrid AE architecture to other malware types; Explore real-time detection and online learning
Sun, Liu & Yue (2019)	Transfer Learning case study; AI-enhanced offloading with service-accuracy optimization; Cooperative Edge–Cloud Intelligent Computing Architecture	Introduces service accuracy as a new metric; AI-based offloading improves performance and reduces latency; Transfer learning shows improved service accuracy	Balancing accuracy and latency in heterogeneous IIoT; Limited computational resources at the edge	Optimize multi-objective offloading; Integrate reinforcement learning; Expand to large-scale IIoT deployments
Qiu et al. (2019)	SIGMM (Spammer Identification using Gaussian Mixture Models); ML-based classification	SIGMM outperforms Reality Mining and Hybrid FCM in recall, precision, and time complexity	Difficulty modeling user behavior variability; Scalability in large mobile networks	Integrate deep learning for dynamic spammer behavior; Expand to IoT communication networks

Kavana & Neethi (2018)	Artificial Neural Network (ANN) feed-forward for defect detection	ANN effectively detects overvoltage, under-voltage, overload, ground fault, and unbalanced voltage; Motor acts as a self-sensing device	Limited dataset from single motor; Generalization to industrial-scale motors uncertain	Extend system to multiple motor types; Use deep learning for more complex fault patterns
Wu & Tan (2018)	Distributed Big Data Platform + Apriori Data Mining Algorithm	Distributed computing significantly improves processing efficiency; Apriori algorithm helps discover load distribution rules and enhances load forecasting	Handling highly heterogeneous data formats; Real-time processing limitations	Integrate advanced ML like LSTM/GRU for dynamic load forecasting; Improve scalability of big data architecture
Kanawaday & Sane (2017)	ARIMA Time-Series Forecasting for sensor data; Predictive maintenance	ARIMA effectively predicts failures and quality issues; Helps improve manufacturing quality and reduce maintenance costs	ARIMA struggles with nonlinear patterns; Requires stationarity; Limited predictive power for complex IIoT data	Combine ARIMA with ML/DL (hybrid models); Move toward real-time predictive maintenance using LSTM
Jiang & Kuo (2017)	Convolutional Neural Network (CNN) Improvement for Predicting Remaining Useful Life (RUL)	CNN-based model achieves superior RUL prediction accuracy compared to existing PHM models	Difficulty capturing long-term dependencies; High computational cost	Apply CNN–LSTM hybrid models; Use transfer learning and domain adaptation for industrial PHM

Conclusion and Future Work

Intelligent decision-making, real-time sensing, and self-directed operations in smart factories are enabled by AI, big data, and the IIoT, which are radically altering the contemporary industrial landscape. The IIoT systems produce high-velocity, heterogeneous and massive data, which interacting with scalable big data frameworks and ML methodologies like Random Forest, SVM and LSTM can be exploited to support the further predictive maintenance, fault diagnosis, and quality optimization. In spite of such developments, IIoT analytics continues to experience major issues such as inconsistency of data, edge-bound computational resources, cybersecurity concerns and insufficient explain ability of the intricate ML models. These barriers have to be addressed to attain complete reliability, transparency, and efficiency of Industry 4.0 ecosystems [26-47].

Future studies ought to be aimed at creating stronger and more scalable IIoT analytics systems that can utilize edge-cloud partnerships that minimize latency and facilitate real-time insight into the system. Advanced data fusion and automated pre-processing methods are needed to process heterogeneous industrial data and explainable AI methods are required to make ML choices more transparent and trusted. Lightweight encryption, federated learning, and blockchain-based mechanisms can help to improve privacy and security and protect sensitive industrial information. Also, models of continuous learning that are not only resistant to concept drift but can adapt to it and models that can generate synthetic data based on digital twins or generative models, have the potential to increase the effectiveness of forecasting and problem identification in dynamic industrial environments. These developments will enhance the credibility and maturity of predictive analytics based on big data in future smart factory.

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