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MULTI LINEAR REGRESSION-BASED IOT AND FOG COMPUTING ON MAINTENANCE PREDICTIONS APPROACH FOR EFFICIENT ASSET MANAGEMENT IN INDUSTRY REVOLUTION 4.0

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ABSTRACT

Industry 4.0 makes it possible for new developments in technology like Big Data Analytics and Machine Learning to be successfully incorporated into and combined with current production processes, allowing smart manufacturing. With the use of predictive maintenance, a company owner can make decisions like replacing or fixing a component before it fails and affects the entire production line. To optimize work distributions and maintenance prediction models, Industry 4.0 (I4.0) necessitates good asset management. The Multi Linear Regression (MLR) based predictive maintenance in IoT and fog computing is presented in this study. The data produced by I4.0's Industrial Internet of Things (IIoT) enables information transparency and process management. Regular maintenance enables the business manager to make choices like when to fix or substitute a part before it malfunctions and disrupts the whole manufacturing process. Thus the study illustrates a forecasting model for predicting rapid failure in industrial machinery and to enable an effective production and servicing process. The outcome demonstrates that the suggested solution performs better than current methods in terms of computational cost execution time, and energy usage. In comparison to the second-best outcomes, the execution period is quicker, the cost is less, and the amount of energy consumption is lower.

Keywords: *Internet of Things (IoT); Fog Computing; Industry 4.0; Asset Management; Multi Linear Regression (MLR)*

1. INTRODUCTION

The phrase I4.0 was initially employed to describe the 4th industrial revolution at the Hannover Exhibition of Industrial Innovations in 2011. In contrast to the third industrial revolution's procedure automation or digitization, I4.0 involves integrating Cyber-Physical Systems, the IoT, and related offerings into key production procedures. Industry 4.0 has been made possible by nine innovations, or "pillars," as well as a significant shift in production and management of human resources, according to a more extensive explanation [1]. In the modern age, manufacturing procedures are being infiltrated by information and communications technologies to create effective "smart factories" that can adapt to changing managerial objectives and market conditions. Additionally, via smart control of processes and administration, Industry 4.0 enables the development of novel business designs, the discovery of improved ones, and the fulfillment of

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an increasing consumer expectation for product customization. The cross-functional interaction between manufacturing and service organizing is an essential component in Industry 4.0, permitting businesses to carry out an economically viable manufacturing process that incorporates maintenance within a pair of the eight key value individuals for the technology, which are "Asset utilization" and "A variety of services and aftersales" [2]. Without a doubt, most industrial maintenance administration is one of the foundational steps that should have been integrated in connection with Industry 4.0, carrying out an important change from the breakdown and regular service to forecasting and preventative repair procedures to achieve technological and economic benefits. Innovative technologies are implemented as part of the shift to Industry 4.0, and production and management of human resources undergo significant transformations as well [3].

The Vertical and Horizontal Systems integrating, Additive Manufacturing, Big Data analysis, Simulations, Cloud Technology, augmented and virtual reality, and information security are among the innovations that make up Industry 4.0. Each of the nine Industrial 4.0 pillars changes the production facility into a "knowledgeable" or intelligent factory that is entirely computerized and incorporated and has a manufacturing procedure that is optimized [4]. Additionally, relationships between manufacturers, vendors, and consumers, and additionally between people and production frameworks, may be developed that are more efficient and inventive. The Internet of Things is expanded into an industrial setting via the Industrial Network of Things. It speaks of a machine-to-machine contact that is conducted without human involvement. The IIoT makes it possible for physical things to communicate with each other via sensing and common internet technologies. Technologies that are a component of the complete supply chain are included in the realized network. Cyber-physical networks, which are mechanisms that offer information processing, communication, and management frameworks, are dependent on the IoT. "The structures within humanly and naturally produced networks that are intimately interconnected with computations, interactions, and management technologies" is how CPSs have been defined. Complicated and diverse infrastructures are combined to accomplish outstanding performance and dependable processes in a smart manufacturing facility.

Following European Standard EN 13306:2017 (1330), "The Maintenance is the culmination of every administrative, managerial, and technical operation throughout the service lifespan of a product designed to keep technology, or rehabilitate technology, a condition that ensures it can carry out its essential activity" Additionally, according to the Standard, maintenance management encompasses a group of tasks "that define the maintenance goals, approaches, and duties, and execute them through such processes as maintenance preparation, maintenance management, and the enhancement of maintenance operations and the field of economics [5]. The activities involved in creating a regular work routine to ensure smooth instrument functioning and avert serious problems are referred to as maintenance preparation. Choosing the best maintenance strategy and planning and scheduling operations are among these duties. In contrast, maintenance supervision and control relate to the different components that should be kept under close watch to guarantee that the management of maintenance is properly implemented in a manufacturing facility [6]. These elements include the gathering of information from the field to track the effectiveness and dependability of resources, work influence and submitting reports, management of inventory, and expenditure calculating and management. Furthermore, because maintenance affects both quality and efficacy, it is crucial to a manufacturing company's performance. Since the management of maintenance links several organizational business operations and processes in a manufacturing facility, its execution is challenging and demands extreme diligence.

To regulate and optimize the utilization of assets and ensure the accomplishment of the company's goals, each system of management consists of an organizational structure backed by three key elements: personnel, processes, and technologies. In terms of the methods, maintenance strategies have changed over time. Traditionally, corrective or reactive repair was the first kind to be used and was driven by the "run-to-fail" concept. The practice of preventive care was eventually introduced when the problem prevention strategy rather than the failure repair strategy was put into place. Both schedule-based management and maintenance based on conditions fall under this group of activities [7]. Predictive servicing, which is seen as its progression since it is concentrated on identifying and avoiding signs of failure or deterioration, is included in the subclass of maintenance based on conditions. Recently,

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additional proactive maintenance theories have been put forth. Employing ICTs-based management instruments and techniques, these theories take into account the potential of modifying the processes to the surrounding's constantly shifting circumstances and lining them up with internal and external specifications throughout the system's entire existence cycle. It is necessary to analyze aspects like human accessibility, supply and demand management, compliance with manufacturing planning, and the arrangement of jobs and maintenance to maximize the effective utilization of capabilities. The administration of tasks specifies and inventories, processes, and technical requirements, arranging and handling of resources, dissemination of assistance demands, tracking and handling of spare components, expense reporting and governing, and dependability assessment instruments are all complemented by the data management system as part of maintaining and along with planning procedures [8]. The necessity for a computerized system that is tightly associated with every key resource of the business, nevertheless, is only one aspect of the role played by technologies. The instruments that operators implement to constantly ensure uninterrupted interventions are another. The operators' position is crucial because they are in charge of performing maintenance tasks and maintaining the understanding base required to ensure the health of the equipment. As a result, maintenance specialists' training is essential when people want to promote the ongoing growth of their abilities and effectiveness.

The Industrial Internet of Things revolution increases networking and computer capacities while reducing the requirement for human engagement in industrial operations and procedures. Employing IoT solutions, however, necessitates a significant transformational procedure that involves not just new products and equipment but also a shift in mentality. It's fascinating how many obstacles faced by businesses looking to build IoT networks made up of scattered edge devices relate to the dangers associated with this rapid shift. One significant obstacle is the IoT implementation's expenditures on investments, which might be prohibitive for small and medium-sized businesses given the uncertainty of the upcoming value chain. [9] Given that it is frequently inadequate to handle the huge array of software and hardware components needed for Industry 4.0 driven by the IoT, it is also important to meticulously evaluate the absence of knowledge and expertise of the present Information Technology employees. It becomes apparent that present ecosystems for IoT suffer from the dispersion of traditional approaches as well as implementation specifications concerning compatibility and accessible standards. Additionally, dispersed IoT structures must smoothly and effectively connect industrial IoT sensors with previous technology that is already installed in the manufacturing facility. Figure 1 depicts the application of IIoT and Fog Computing.

Given the enormous volume of information created by a wide range of sources, confidentiality, safety, and management are particularly crucial [10]. The ownership of information raises a lot of concerns, thus secure communication must be ensured, especially for sectors whose items and possessions are crucial in these circumstances. To operate effectively towards assaults based on unauthorized alterations, injections, or elimination of business information throughout their existence, forecasting techniques must be supplemented by systems and mechanisms that provide authorized sensors access as well as information encryption, identification, and reliability confidence. The digitization of manufacturing goods, procedures, as well as services, is poised to increase efficiency, satisfaction, and revenues through solutions based on information since the necessary data collection systems are already in existence. However, there remains a wide gap to be bridged between real industrial equipment and their digital twins which are required, among other uses, to develop optimized maintenance/operation decisions in regards to their prediction [11]. Yet there remains a significant gap connecting actual manufacturing machinery and its computerized duplicates that has to be closed to design optimized servicing and operation choices based on the technology's anticipated prediction. Additionally, statistics are frequently employed when a field engineer services the device. In numerous industrial areas, full incorporation of edges and cloud-based computing techniques is still unknown. As a result, Industry 4.0's digitalization processes might be sparked by the growth and relatively improved sophistication of fog computing frameworks, which can also effectively enable IoT applications.

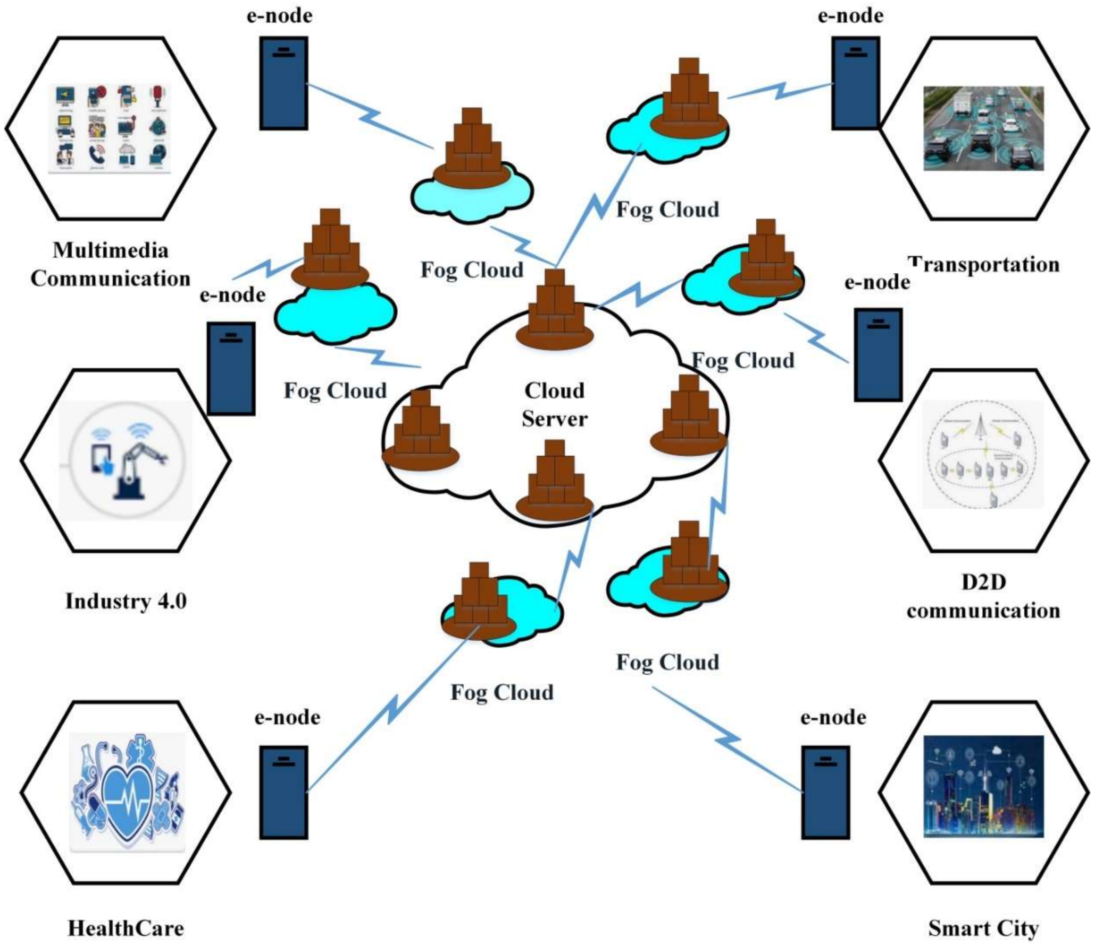

Figure 1: Application of IIoT domains and Fog computing

The key contribution is the suggestion of an Industry 4.0 framework that integrates predictive algorithms into an Internet of Things (IoT) approach and fog computing. As a result, the study offers a unique framework that integrates the benefits of the mentioned technologies while also offering potential sectors an energy-efficient choice. Several different industries, like healthcare, industrial, oil and gas, and many more, have embraced IoT. To maximize equipment uptime, the objective is to foresee issues before they arise. Many various sectors, such as medical care, commercial, oil and gas, and many more, have embraced IoT. The major objective is to anticipate equipment faults and increase the availability of equipment. Organizations attempt to increase operational and production dependability, security for employees, and profitability in today's extremely dynamic business environment. Several industrial organizations have yet to utilize big data and ML analytics because there is a lack of complex analytical instruments and abilities. The remaining sections of the paper are structured as follows. Literature reviews are included in Section 2. Section 3 presents the suggested MLR-based predictive maintenance in IoT and fog computing. In Section 4, the effectiveness of the suggested algorithm is confirmed. In Section 5, the research is completed.

2. RELATED WORKS

Technology advancements in fields like networking, handling information, computation on computers, and communication are rapidly establishing the IoT architecture throughout businesses in many industries. As networks transition into cyber-physical networks of systems in the setting, linked components produce enormous amounts of information that are often transmitted to a centralized node for additional processing. Processing of information, particularly and especially about the industry of manufacturing

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can offer insight into the operational state of the organization or procedure being watched. To develop such understandings and allow decision-making based on data, however, approaching instantaneous limits. The present research addresses a fog computing framework for allowing maintenance-connected forecasting analysis in the manufacturing sector utilizing a two-step technique: (1) model development on a cloud platform, and (2) Model implementation on the edge, which is enabled by the IoT for intelligent manufacturing. A real-life scenario from the robotics sector has been employed to evaluate the suggested methodology [12].

The flow of value of manufacturing items needs to be optimized if firms are to remain competing in an increasingly accessible international marketplace [13]. Industrial IoT has arisen inside the framework as an innovation seeking to achieve outstanding efficiency in manufacturing. As smart management of maintenance is essential to ensuring efficiency, a smart manufacturing approach additionally asks for management. IIoT applications are often finished employing cloud computing to provide services that are required. In the work, researchers contend that the demands of maintenance procedures cannot be fully met by cloud computing alone. The study noted many of these demands. Then, as the latest innovation in the IIoT, researchers suggest a platform leveraging fog computing to improve smart maintenance administration. Additionally, the study discusses the platform's capacity to meet the outlined needs.

Investigating industrialized asset management during production is the goal of the project. After highlighting the needs for AM in the industry, the importance of understanding as a crucial factor is taken into account to provide an overview of difficulties and suggestions for further growth. The research is supported by a thorough, comprehensive literature evaluation. The descriptive statistics are offered for the qualifying papers and an analysis of content is carried out, both employing an industry-independent prescriptive-based methodology of assessment. The criteria used to categorize 10 areas of importance for AM in manufacturing include AM concepts, organization, and data. The main issue with implementing AM successfully is information. Additionally, the Internet of Things, data modeling purposes, ontology engineering, and big data analytics are the primary innovations anticipated to promote the use of additive production in manufacturing [14]. Further study on the application of additive manufacturing in producing goods, with a particular emphasis on data and information management, may be stimulated by the problems highlighted and recommendations for future improvement. The sector-independent normative-based paradigm may also make it possible to assess AM in various application situations, facilitating comparisons across sectors. -Industries with greater operational threat, such as infrastructures and natural gas and oil, have made significant strides in additive manufacturing, whilst those in the manufacturing sector have lagged. The current state of the art is shown in this first-of-its-type literature review on additive manufacturing, which paves the path for additional studies and developments.

Within the framework of the Industry 4.0 model, the machine learning sector has had a significant influence on the manufacturing sector. The Industry 4.0 framework promotes the use of intelligent sensors, equipment, and gadgets to allow intelligent manufacturing facilities that continually gather production-related data. By processing the gathered data to boost production productivity without drastically altering the needed resources, ML approaches enable the development of relevant insight. Furthermore, the capacity of machine learning techniques to deliver predictive information has made it possible to identify complicated manufacturing structures and provides an approach for a system that supports intelligent decisions in a wide range of manufacturing obligations, such as smart and perpetual evaluation, anticipatory maintenance, enhancement of quality, procedure optimization, management of supply chains, and scheduling tasks. Even though various machine learning approaches have been applied in a range of manufacturing applications throughout the past, there are numerous unresolved inquiries and difficulties, ranging from issues like cloud computing and cyber-security to issues like big data collection, and storage spaces. and comprehending, as well as information reasoning that enables real-time actionable intelligence. As a result, the primary objective of the special issues is to gather together a wide spectrum of academics to describe the most recent work in the core fundamental as well as empirical elements of ML and its applications in production as well as manufacturing systems [15].

The IoT is the fundamental component of Industry 4.0 for cyber-physical systems, which was developed in the last decade to enhance the industrial environment. As a result, the use of the Internet and CPS in practical electrical devices and

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systems has increased [16]. The greatest obstacle to IoT deployment against cyber-attacks, meanwhile, is cyber security. This study makes a novel IoT architecture recommendation based on using ML techniques to prevent cyber assaults and provide dependable and safe internet-based monitoring for the state of inductive motors. Here, powerful ML algorithms are used specifically to accurately identify cyber-attacks and motor health. The suggested architecture uses low-cost channels of communication and a connection to the internet to confirm the motor condition while requiring less labor to join diverse networks. To accomplish this, the CONTACT IoT elements framework is used to create an interactive dashboard to display the machine learning-based information being processed. The suggested IoT platform based on ML would immediately visualize fake information displayed on the IoT platform dashboards once the indication for cyber-attacks has been recognized. To highlight the effectiveness of the recommended IoT architecture, many practical situations with data collecting are conducted. The findings show that the suggested IoT architecture, which is based on ML, can efficiently visualize various motor status issues as well as cyber-attacks on the networks. Additionally, on the user interface of the suggested IoT platform, all errors in the motor position and false information caused by cyber assaults have been effectively identified and visualized with a precise and clearer visualization, improving the ability to make decisions regarding the motor position. Additionally, the newly proposed IoT architecture's RF algorithm offers exceptional accuracy of 99.03%, which is much higher than existing ML algorithms, for the identification of motor failures caused by vibration underneath industrial circumstances. Additionally, the suggested IoT has minimal latencies to detect motor defects and assaults and display them on the IoT platform's primary dashboard.

The main objective of the paper is to propose approaches that collect information and knowledge and offer support for asset-related decisions in a range of industrial maintenance jobs. The primary objective of the study focuses on identifying customer requirements and considering how to meet those demands. Researchers provide a realistic MS Excel proof of concept that depends on the idea of information-based management of assets, a method that emphasizes the extensive utilization of evidence from several information sources. End interviews with users and the outcomes of the following assessment conversations, in which a prior stage of the POC was evaluated, were used to generate the specifications for the POC. The criteria included things like using artificial intelligence and implementing visual features. In the essay, researchers go through ways to meet these needs and provide a software solution. Additionally, the study will investigate the solution's viability in asset management organizations from a perspective of information management standpoint [17].

Technologies related to Industry 4.0 present vital prospects for subsequent development and corporate expansion. Industry 4.0 is being implemented using cutting-edge technology including artificial intelligence, IoT, big information, ML, and various other emerging technologies [18]. The essay examines how Industry 4.0 innovations support the development of sustainable environments in manufacturing and other sectors. The surroundings should benefit from Industry 4.0 technology and the critical relationships created by cutting-edge technologies. Manufacturing is closely connected to communication and information systems in the era of I4.0, which increases its scalability, competitiveness, and expertise. With the implementation of adaptable robotics, data, and technology for communication, I4.0 provides a variety of concepts, guidelines, and technologies for building novel and existing manufacturing facilities, allowing customers to select alternative designs at production rates. To enhance environmental sustainability, the article outlines tools and aspects of I4.0 and studies the significant advantages of I4.0 for environmentally friendly production. The research, which is based on a literature assessment, aims to determine how I4.0 technologies might enhance environmental sustainability. Additionally, it describes how I4.0 might address environmental issues. The identification and discussion of twenty key I4.0 applications for building sustainable environments are mentioned. The manufacturing environment, supply networks, distribution channels, and market outcomes are thus better understood as a result. In general, Industry 4.0 technology appears to be ecologically friendly while producing items more effectively and using fewer resources.

Manufacturers anticipate Industry 4.0's added value as the world undergoes a digital transition. The IoT has the capability to less costs, increase effectiveness and value, and provide data-driven maintenance prediction products and services, according to studies. Sensors, reliable connectivity, and unified addition are needed for the storage of a wide range of actual data from goods including the environment. Smart appliances for homes are emerging thanks to IoT, a crucial I4.0 enabler, for increased consumer happiness, energy efficiency, personalization, and sophisticated big data analytics. To alter the stalled production lines and satisfy consumer demands, however, is a struggle for established enterprises with few assets. By converting traditional household equipment into IoT-enabled smart systems that may be incorporated into a system for smart homes, the study [19] seeks to close the gaps. An industry-led investigation explains how to use cutting-edge Industry 4.0 technology to transform traditional appliances into smart products and systems (SPS). The scope of this study, nevertheless, is only one vendor's line of home appliances. While connecting smart home appliances with a mobile app is a practical smart home solution, this industry-based development effort does not provide connectivity to other smart home appliance manufacturers.

Due to the rapid expansion of the Internet of Things (IIoT) rapid expansion, several sources are continuously producing a sizable volume of data. Given that the energy and storage capacities of IoT end devices were rigorously capped, it is not advisable to store all the raw data permanently. The networks could be installed in isolated, unmanaged regions, making the devices unstable and open to several dangers., The paper [20] covers the new issues in IIoT data processing, secure storage of information, effective data retrieval, and dynamic data gathering. Then, by fusing cloud and fog computing, we provide an adaptable and affordable framework to address the issues raised above. The acquired data is processed and saved by the edge server or the cloud server depending on the time delay needs. In particular, the edge server preprocesses all of the unprocessed data first, after which the time-sensitive data including controlling data is used and stored locally. To facilitate future data collection and extraction, the non-time-sensitive data such as monitored data are sent to the cloud server. To assess the effectiveness of the plan, several simulations and experiments are run. The outcomes show that the suggested structure could substantially improve the IIoT's data storage and collection's effectiveness and security.

3. PROBLEM STATEMENT

The issues in conventional mechanisms revolve around the challenges and opportunities presented by the rapid integration of IoT and Industry 4.0 technologies in various industries, particularly manufacturing. These technologies have led to the generation of vast amounts of data from interconnected devices and systems. The primary problem addressed is the need for efficient data processing and management in this context. Traditional centralized cloud computing approaches are often insufficient in handling the scale and real-time requirements of data analysis and decision-making. Additionally, the research highlights challenges related to data, information management, cybersecurity, and sustainability in the context of Industry 4.0 and IoT adoption. The goal is to optimize manufacturing processes, enhance environmental sustainability, and transform traditional appliances into IoT-enabled smart systems while addressing data storage, processing, and security concerns [19]. The proposed solutions aim to leverage machine learning, big data analytics, and innovative architectures to tackle these issues effectively.

4. RESEARCH QUESTIONS

- How can MLR be effectively employed in predictive maintenance within the context of Industry 4.0 and the IIoT to improve asset management and optimize work distributions in manufacturing processes?
- What are the key parameters and data sources required for developing accurate predictive maintenance models and how can these models be integrated into existing production and servicing processes?
- How does the proposed MLR-based approach in conjunction with fog computing and IoT technologies compare to existing methods in terms of computational cost, execution time, and energy consumption, and what are the implications for its practical implementation in smart manufacturing environments?

5. PROPOSED METHODOLOGY

5.1. Dataset

Data of qualities are expressed by generic words and numeric numbers in the datasets utilized for the present study, which also includes organizational privacy and proprietary information. The dataset includes eleven characteristics that describe the state of manufacturing machinery, including the date and time of the recording, the machine ID such as an actual asset verification number, the error message, the voltage of the electricity in volts, the rotational velocity, the observed pressure, the determined motion, the parts that have been repaired, the kind of machinery, the

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machinery's condition, and the malfunctioning rate, which ranges from 0 to 1. The collection of data is extremely unbalanced, though, with 280,006 instances of class "0" and 6,663 examples of class "1" (2.20%). requiring any training, the data set with imbalances can offer an extremely accurate system. The under-sampling approach is then employed when analyzing the collected data to address the issue of imbalance. The largest class is periodically reduced using the under-sampling approach to correspond with the minority class in terms of numbers. As a result, there are now 12,480 samples total, with 6,555 data of class "1" and 7,700 data of class "0".

5.2. System Architecture

Figure 2 depicts the proposed management of the assets system structure. The framework is organized into 5 layers based on their functionalities: the layer of asset, a layer of vision, the layer of network, a layer of fog nodes, and a layer of cloud computing.

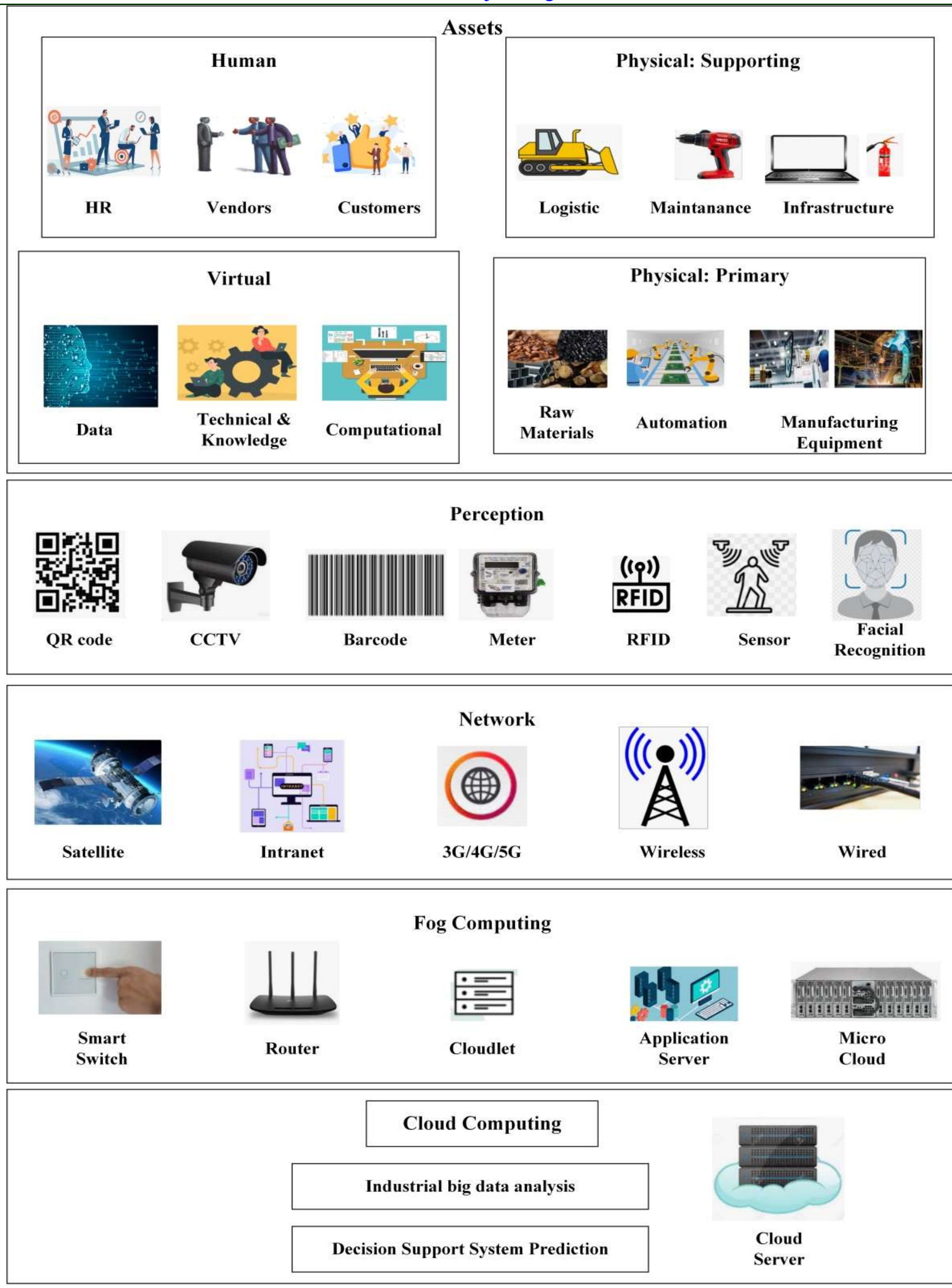

Figure 2: Framework of assets management

5.2.1. Asset layer

Each of the assets that the company owns and expects to generate values is contained in this layer. Major physical, secondary physical, digital, and human assets are all listed as assets. The essential components needed for production and the manufactured goods are known as primary physical assets. The main components are various production and automated equipment, which vary depending on the industry. The components that make and maintain the core manufacturing procedure are known as supportive physical assets. Using the incorporation of computer programs, digital resources allow digitalization in the business and production process. Humans play a direct role in every stage of the life cycle of produced goods, including employees, suppliers, consumers, and end users. Manually functioning, servicing, and problem-solving tasks that are unable to be completed by automated technology require the assistance of employees [21].

5.2.2. Perception layer

Industrial smart sensors are used to collect data about the environment and products [22]. Physical characteristics can be detected and sent for service prediction using industrial smart sensors with meters put in the machinery. The QR code and barcode, which include sensitive information about the assets such as category, place, day of buying, etc., can be read by vision detectors. By lowering time fraud and staff access control, recognizing faces makes human resource administration simpler.

5.2.3. Network layer

It is responsible for relaying actual data from sensing to network hardware, cloud computing, and computer layers [23]. Using satellite connections, owners of companies with numerous manufacturing facilities throughout the world may remain connected to a worldwide company. Assets inside the company can communicate with one another using wireless, wired, and intranet connectivity.

5.2.4. Fog computing layer

Among devices at the edge and the cloud data center, connectivity is established [24]. A distributed, decentralized technology called fog computing allows data to be sent to a server for local processing. Because fog computing has lower latency and bandwidth connectivity than the cloud, it makes it possible to use real-time assets for applications involving analysis. Smaller data centers called cloudlets and micro clouds are located at the network's edge. Digital facility management can produce a sustainable and environmentally friendly environment with the help of the smart switch. The application server, in the meantime, enables the server to independently run software that is specific to the industry. Numerous IIoT applications, including data collecting, smart meters, and distribution technology, are made possible by the router at fog computing capabilities.

5.2.5. Cloud computing layer

It enables the processing of activities related to resource management, industrial big data, and IIoT [25]. Because of the cloud's versatility and pay-as-you-go paradigm, pre-processing, training, testing, estimation, and implementation of models of industrial big data can be carried out at this level. The cloud enables managing assets and scheduling following corporate guidelines.

5.3. Multi Linear Regression (MLR) in IoT and fog computing

The amount of time it took the fog application to execute depended on the CPU's use, its mobility, its network interactions, and its response period [26]. The variable that depends in this instance is the application time to execute, which is reliant on four additional factors that are dependent, including CPU utilization, movement, communication over the network, and reaction time. Consequently, using the subsequent multiple linear regression Eq.1, the study can forecast the length of an application's performance.

$$Tp_i = \alpha_0 + \alpha_1 CPU_{u_r} + \alpha_2 D_{m_r} + \alpha_3 N_{c_r} + \alpha_4 S_{t_r} + er \quad (1)$$

The multiple linear regression approach is selected because it allows for the estimation of application processing time from a variety of quantitative independent variables. Due to the presence of numerous independent factors, simple regression is unsuitable.

The projected time of execution for application i is represented by Tp_i in the equation given. Every dependent variable is equivalent to zero, and the predictive model's intercepts, or value, is represented by the number 0 (or 0). The CPU usage for devices r for application i is expressed as $\alpha_1 CPU_{u_r}$. Device adaptability for equipment r for application i is known as $\alpha_2 D_{m_r}$. The network communications and response rates for device r along with application i, accordingly, are represented by $\alpha_3 N_{c_r}$ and $\alpha_4 S_{t_r}$. The model's coefficients, 1, 2, 3, and 4, define the suggested model while determining the slope of the regression line. er is the error rate, which indicates how different the suggested regression structure is from the actual observational data.

On the contrary, the supply of power affects whether or not a work can be finished with the specific IoT and Fog assets. As a result, the availability of electricity can be regarded as a binary predictor variable, either positive or negative. Also referred to as power profile, the energy usage habits of the devices as well as the applications have an immediate effect on the distribution of resources that are energy-conscious. The regression model will operate as follows after taking power supply and consumption patterns into account in Eq.2:

$$Tp_i = \alpha_0 + \alpha_1 CPU_{u_r} + \alpha_2 D_{m_r} + \alpha_3 N_{c_r} + \alpha_4 S_{t_r} + \alpha_5 P_{a_r} + \alpha_6 E_{u_r} + er \quad (2)$$

Where, for the application i, $\alpha_5 P_{a_r}$ and $\alpha_6 E_{u_r}$ represent, accordingly, the power accessibility and consumption of energy patterns in the device r. For energy-conscious allocation, however, the regression framework in Eq.3 will be utilized.

$$Ap_i = \alpha_0 + \alpha_1 CPU_{u_r} + \alpha_2 D_{m_r} + \alpha_3 N_{c_r} + \alpha_4 S_{t_r} + \alpha_5 P_{a_r} + \alpha_6 E_{t_r} + er \quad (3)$$

The projected consumption of energy for i is represented by Ap_i in the Eq.3. The application time of execution $\alpha_6 E_{t_r}$ is for the r device, application i. The most suitable device for both Tp_i and Ap_i can be determined by applying the following eq. 4 and 5.

$$P_{id} = Miinimum\ (Tp_{i1,} Tp_{i2}, Tp_{i3}, \dots Tp_{in}) \quad (4)$$

$$P_{ie} = Miinimum\ (Ap_{i1,} Ap_{i2}, Ap_{i3}, \dots Ap_{in}) \quad (5)$$

The asset that best satisfies the time limit is P_{id}, while the asset that best meets the consciousness of energy is P_{ie}.

5.4. Communication Model

The study offers the communication architecture that has been proposed and was created to reduce the energy costs for Internet of Things nodes. As a result, energy consumption could be reduced, in part because sending data requires more energy than obtaining it. The fog layer can generate an algorithm for prediction after a training period using data from sensors gathered from end nodes. This model predicts trends in the future, allowing sensors to relay information only when necessary. Following the creation of the framework, the predictive model sends the predicted data to the connected devices. The broker continues to run the model if the discrepancy between the anticipated data and the actual data is smaller than a predetermined value. However, if the predetermined limitation exceeds, the sensor informs the broker of the actual value and modifies the algorithm that forecasts it. Finally, the outcome appears to be more successful if the forecast strategy is more correct.

6. RESULT AND DISCUSSION

6.1. Performance Metrics

A machine learning-based maintenance prediction strategy for the best asset management in Industry 4.0, that utilizes IoT and fog computing.

6.1.1. Time of execution

The time needed to complete a task is called the processing time. Eq.6 can be used to determine the amount of time among the task processing start time (S_t^i) and task processing end time (F_t^i).

$$T_t^i = F_t^i - S_t^i \quad (6)$$

In the equation above, i represents the Fog device used for the execution of the task, and T_t^i denotes the task's processing time.

6.1.2. Cost

For processing charges, messaging and network costs are taken as a factor. Such costs follow the AWS IoT price structure. For communications, the price ranges from $1 to $1.65 per million communications, as well as for communication, it ranges from $0.08 to $0.132 per million minutes depending on the location. The processing cost can be computed as follows:

$$C_t = \sum_{k=x}^{n} C_m + C_l \quad (7)$$

C_m stands for messaging cost, C_l for connection costs, and C_t for overall processing cost in the equation above. The study determined the cost for Fog Devices x through n.

6.1.3. Energy consumption

When determining the best Fog equipment for the application's operation, energy-aware allocation of resources only takes into account the Fog device's energy consumption.

$$E_u^i = \frac{w_t^i}{v_t^i} * F_t^i \quad (8)$$

E_u^i stands for the energy used in the transmission from the end equipment to the fog server, w_t^i assigned for the workload of the task, v_t^i as the processing speed of the task.

6.2. Simulation Parameter and Experiment

The parameters utilized for the simulation are shown in Table 1. On a publicly available data set that incorporates measurements from a combined power plant, the estimation methods in this paper have been put to the test. The models, like in the prior research, depend on an examination of the suggested approach with the MQTT protocol usage, both using MQTT's three unique QoS levels.

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The energy costs have been determined for different levels of error (in this instance).

Table 1: Parameters used for simulation

Device Configurations	Descriptive value
RAM	2048
Bandwidth	10000
Hosts	1
Processing Elements	1
Instructions	2500-5000

The outcomes obtained with different ML techniques are comparable, except for linear regression which is less accurate. It's important to note that various prediction methods have various computational requirements. But because this approach depends on fog computing, it allows network accessibility, allowing the algorithms for prediction to be set up regardless of the fog layer, according to the accuracy requirements.

The assignment of operational obligations to the Fog infrastructure is the primary objective of this study. Various assessment possibilities were utilized throughout the experiment. In the beginning stage of the first assessment, 70 applications had been submitted to the Fog environment; after that, the quantity gradually climbed to 560 applications. For this assessment scenario, the cost, the processing time, and the energy usage is calculated. In the second assessment, when there were more applications submitted. Each variable user and device variable was changed in the previous assessment. Changes in user time constraints, available resources, battery life, and CPU utilization were among these dynamic elements. The other variables utilized to predict active user behavior, battery, distance, and changes in CPU accessibility are given in Table 2.

Table 2: Prediction parameters

Parameters	Descriptive variables
Distance	5-50m
Battery	30%-80%
Availability of CPU	40%-120%
Deadline tasks	5
The task for each app	12
CPU variation	15%-45%

6.2.1. Analysis of Energy usage and efficiency

Table 3 contrasts the energy consumption and performance of WiFi (IEEE 802.11) and Long-Term Evolution (LTE) 4G, two wireless technologies.

Table 3: Energy utilization and performance of the protocol

Protocols	Energy utilized	Efficiency
4G	2.90 Watts	1.9 micro bit
WiFi	393 Watts	1.3 micro bits

The amount of bytes needed to transmit a single MQTT message was determined. The tests were run with QoS 0, 1, and 2 enabled by employing the SSL/TLS cryptographic protocol. Each of the emails has been sent with the same payload and subject. The experiment's results are displayed in Table 4.

Table 4: Publishing of MQTT with message

QoS	TCP	PUB	PUB_{ack}	PUB_{rel}	PUB_{rel}	PUB_{com}
0	65	138	-	-	-	-
1	65	140	98	98	98	98

6.3. Training and Testing Accuracy

To forecast the state of manufacturing machinery, logistic regression is used in equipment maintenance predictions. AUC that is similar to 1 is a better indicator of separateness, whereas AUC = 1 indicates that the classifier perfectly distinguishes between all positive and negative categories. The performance matrix and associated training and testing dataset measurements are shown in Table 5.

Table 5: Confusion matrix of the training process

Measures	Training	Testing
Accuracy	0.960	0.950
Precision	0.958	0.956
Recall	0.952	0.944
F1-Measure	0.950	0.940
Threshold	0.5	0.5
AUC	0.991	0.982

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6.3.1. Execution time

When compared to existing techniques, MLR's execution time is faster. The adaptability of parameter adjustment is what makes MLR's execution time substantially shorter. The algorithm exhibits the shortest execution time among every one of them and can find the solution faster because of the acceleration in all iterations. Figure 3 shows the execution time of MLR with existing approaches

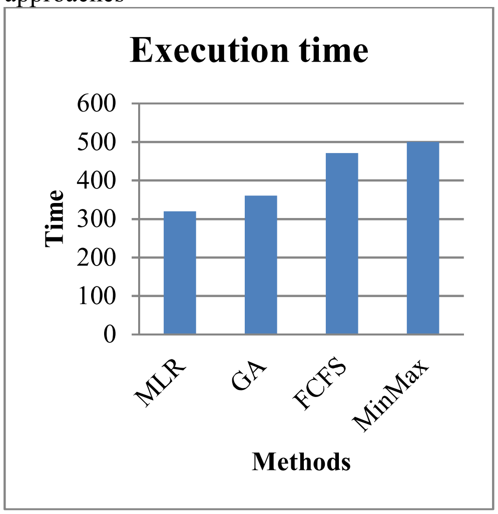

Figure 3: Execution Time

6.3.2. Cost

Comparing MLR to current methods, the price is cheaper. Tasks are distributed correctly and more efficiently using MLR. Thus, this significantly lowers the cost of execution. Figure 4 shows the cost of MLR with existing approaches.

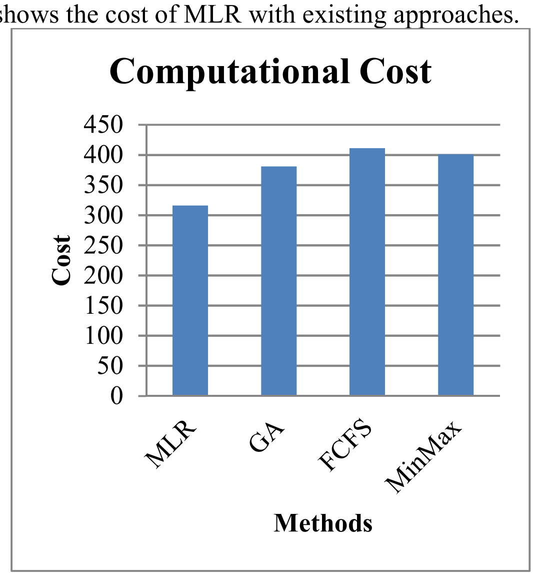

Figure 4: Computational Cost

6.3.3. Energy usage

When compared to current methods, MLR uses less energy. The label-based clustering feature of the workflow enables similar jobs in the process to be grouped. Clustered workloads, which are run instead of individual workloads, use less energy while lowering network traffic. Additionally, the MLR method promotes grouping highly computational operations in cloud nodes that require a lot of resources and simpler ones in edge devices. As a consequence, energy usage is lower. Figure 5 shows the energy utilization of MLR with existing approaches

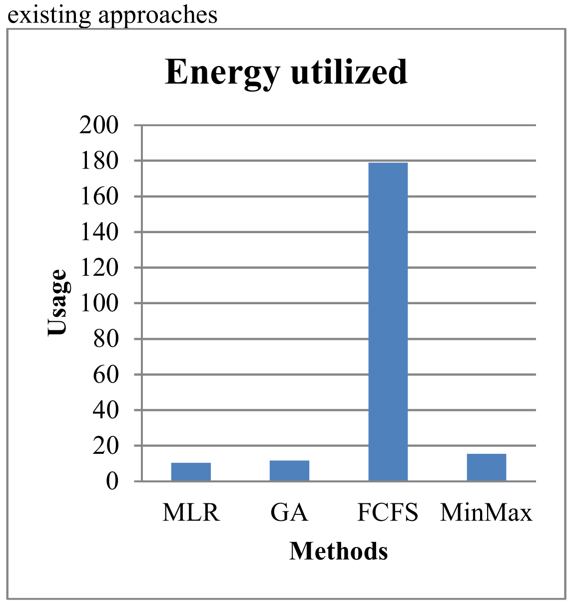

Figure 5: Energy Usage

Execution time, cost, and energy were the performance indicators for the evaluation. A thorough simulation experiment showed that MLR performed better than existing methods in terms of having the least amount of energy used, cost, and execution time.

7. CONCLUSION

Smart manufacturing is made feasible by Industry 4.0, which enables new technological advancements like Big Data Analytics and Machine Learning to be effectively incorporated into and merged with existing production processes. A business owner may choose to replace or repair a piece of equipment before breaks and impacts the whole manufacturing process by using preventative maintenance. I4.0 demands efficient asset management to optimize employment maintenance and distribution models for prediction. The paper presents the Multi Linear Regression (MLR) based

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predictive maintenance in IoT and fog computing. Transparent data and process management have been rendered possible through the IIoT, a component of Industry 4.0. Regular maintenance gives the company manager the ability to make decisions like when to replace or fix a part before it breaks down and messes up the entire production process. To demonstrate an approach to prediction for predicting rapid breakdown in industrial machinery and to make the manufacturing and upkeep process more efficient. The findings demonstrate that the suggested solution outperforms existing techniques in terms of computational cost, execution time, and energy usage. The execution time is shorter, the cost is lower, and there is less energy usage in comparison to the second-best results. Following training and testing, the prediction efficiency of the approach was 96% and 95%, respectively.

The MLR-based predictive maintenance approach, within the framework of Industry 4.0 and smart manufacturing, demonstrates considerable promise, but several challenges and opportunities for improvement remain. To address emerging challenges and enhance the system, advanced machine learning techniques like deep learning and ensemble methods could be integrated for more accurate predictions. Real-time data integration, anomaly detection, and edge computing solutions should be explored to ensure timely decision-making and adaptability to changing data patterns. Additionally, robust cybersecurity measures, continuous monitoring, and a focus on data quality and governance are essential for maintaining the system's reliability and integrity. Promoting human-machine collaboration, conducting cost-benefit analyses, and facilitating knowledge transfer within the organization will contribute to the long-term success of predictive maintenance in smart manufacturing.

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