International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 16, No.1 (Aug-24)

http://dx.doi.org/10.12785/ijcds/160151

Optimizing Resource Allocation in IoT for Improved Inventory Management

Arti Kotru[1,2] **and Isha Batra**[3,*]

[1]School of Computer Applications,Lovely Professional University, Phagwara, India
[2]P.G. Department of Computer Applications, Model Institute of Engineering and Technology, Jammu, J&K, India
[3]School of Computer Science and Engineering,Lovely Professional University, Phagwara, India

Received 9 Nov. 2023, Revised 28 Apr. 2024, Accepted 1 May 2024, Published 1 Aug. 2024

Abstract: Effective inventory management is crucial for businesses to minimize costs and maximize operational efficiency. This paper explored the optimization of resource allocation on the Internet of Things (IoT) for improved inventory management and developed an inventory management system using IoT and Wireless Sensor Network (WSN) to optimize the resource allocation. In this paper, the dataset that is taken into consideration is the primary dataset, which is collected from different locations with the help of WSN, temperature, humidity, and stock of mapping of the place where data is allocated. Further, preprocessing of the data is done, and then the data is split as training and testing data. Machine learning models, i.e., decision tree, random forest, regression model, and ensemble model (combination of decision tree, random forest, and regression model), are applied to classify and train the data. The novelty of the research is establishing an inventory management system employing IoT and WSN, combining machine learning and ensemble models for resource allocation optimization, and outperforming traditional approaches. The result metrics such as Root Squared Mean Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Accuracy are taken into consideration to evaluate the performance of the model. Experimental results are obtained the values of RMSE, MAE, and MSE are 0.25, 0.0625, and 0.625, respectively. Also, the overall accuracy of the proposed model would be obtained as 93.75%. The comparative analysis shows that the proposed model outperformed the existing conventional model in terms of accuracy.

Keywords: Inventory Management, Internet of Things, Wireless Sensor Network, Resource Allocation Optimization, Machine Learning, Decision tree

1. Introduction

Today, successful businesses require efficient inventory management. Operating efficiently and having timely access to the right goods and resources could make or break a business. Here, the Internet of Things (IoT) has shown a new era of inventory management, allowing for unprecedented resource allocation optimization. To better manage inventory resources, businesses could use IoT devices, data analytics, and real-time monitoring. Innovative technologies are needed to achieve operational excellence and a competitive edge in supply chain management. Business inventory management has been transformed by the IoT, which optimizes resource allocation in real-time [1]. For higher productivity, lower costs, and happier customers, Internet of Things-based stock management is being promoted. With IoT devices and data analytics, businesses could better manage stock, allocate resources, and adapt to changing customer preferences. IoT has impacted stock management, as is well known. Better inventory tracking, fewer stockouts, and fewer surpluses are among its suggested benefits, according to extensive research [2]. IoT data-driven decision-making helps firms distribute scarce resources like labour, storage space, and vehicles. Radio Frequency Identification (RFID) and other wireless, mobile, and sensor devices have made durable industrial systems and applications possible thanks to the IoT. Recently, industrial IoT applications have been developed [3]. IoT, an emerging technology, is gaining popularity. The IoT envisions a network connecting all physical objects to share information about themselves and their surroundings. IoT platforms could improve lives by linking all things collectively. Many collaborative IoT applications, such as smart homes, medical facilities, vehicle-to-vehicle, and vehicle-to-person traffic control, are emerging [4]. The importance of technical advancement and operational effectiveness in today's fiercely competitive business environment inspired the selection of "Optimizing Resource Allocation in IoT for Improved Inventory Management" as the conference's theme. Costs, customer satisfaction, and the bottom line are just a few of the areas that inventory management could affect directly. The IoT presents a once-in-a-generation chance to radically alter the way essential resources are distributed in this field. Investigating and

E-mail address: arti.mca@mietjammu.in, isha.batra2487@gmail.com

learning about the use of IoT technology in inventory management could help businesses become flexible, save money, and make educated decisions based on data. This is a topic that is both relevant and potentially transformative, with the potential to alter standard inventory procedures and open the door to long-term success in the business world.

A. IoT in Inventory Management

The term IoT refers to a network of billions of connected physical objects that collect and exchange data about their usage and surrounding conditions. Sensors are always updating the network with information about the devices' current states of health. The Internet of Things allows machines to automatically share information in real-time. Inventory management is an integral aspect of supply chain management (SCM) since it has implications for both production and price. Inventory management's goal is to optimize customer satisfaction at the lowest possible cost, and this is achieved through careful planning of inventory replenishment strategies [5]. It is the goal of inventory management to minimize stockouts and maximize returns from satisfied customers through careful planning and control of inventory levels. When and how many orders should be placed, given supply lead time, on-hand inventory, etc. The traditional methods of inventory management have been put to the test by the new technologies of Industry 4.0. As new technologies emerge, it would be necessary to develop and test novel models and methods for determining inventory replenishment policies [6].

1) Impacts of IoT on Inventory Management

IoT has transformative effects on inventory management, bringing many benefits that change inventory practices. Some major impacts (as shown in Figure 1):

Figure 1. Impact of IoT on Inventory Management [7]

1) **Real-time contribution to the efficient supply chain:** Technology employed by IoT devices allows for completely hands-free data collection. Inventory management is a crucial facet of supply chain management (SCM), as it encompasses all organizational stock-related decisions [8].
2) **Management Warehouse:** The Internet of Things (IoT) and 5G wireless technology improvements are helping to improve warehouse management logistics. The goal of warehouse management is to maximize storage capacity. Warehouse inventory is managed with the use of a computerized warehouse management system [9].
3) **Artificial Intelligence (AI) Algorithms:** The advent of AI has allowed the development of sophisticated algorithms that could handle stocks considerably more efficiently than any human could. With the development of deep learning technology, there has been a resurgence of interest in the potential of AI in the medical field [10].
4) **IoT offers accurate location monitoring and improved inventory tracking:** Products equipped with IoT labels could streamline logistics, as The Daily Plan IoT claimed. This aids in both normal preparation and the search for ways to speed up the supply chain in the event of an emergency.
5) **Better Lead Management:** Estimating the time it would take to assemble all the components needed for manufacturing is made much easier with the help of IoT-based inventory tracking. Changing the focus from managing leads to managing patients with implants is a major paradigm change [11].

B. Importance of Resource Allocation in IoT

The goal of resource allocation in the IoT is to maximize the performance of IoT systems and applications by equitably distributing and optimizing available resources. Resources include everything from data storage space and processing power to electricity and sensors. IoT solutions' performance, scalability, and cost-effectiveness are all strongly impacted by how well resources are allocated [12]. The efficient distribution of devices and sensors to collect data from optimal locations and times is a cornerstone of IoT resource allocation. To do this, need to figure out where to put sensors so that the most useful data can be collected, be it about the environment for smart cities, machines for industrial IoT, or health for healthcare applications [13]. Managing the network bandwidth required to transmit data from these sensors is also an important aspect of resource allocation, especially when dealing with the massive amounts of data created by many IoT devices. Allocating computing resources for data processing and analysis is another critical aspect of resource allocation. For timely insights and decisions, it's essential to provide sufficient computational power and storage capacity to analyze the massive amounts of data produced by the IoT. To minimize delays and maximize throughput, it is common practice to locate edge computing resources adjacent to the data source. Energy management is an additional crucial aspect of IoT resource allocation for battery-operated devices [14]. By minimizing energy consumption with methods like low-power modes and data compression, IoT devices could last longer without being recharged or having their batteries replaced [15].

1) Role of IoT Devices

The world is rapidly transforming in response to the rapid development of technology to meet forthcoming challenges and move toward automation. Towns are transforming into smart cities because of the widespread adoption of various IoT devices, which connect every event to the network. Intelligently, the IoT devices record and transmit data about every occurrence [16]. The rapid expansion of the internet over the last two decades has produced far-reaching, positive effects on economies and societies worldwide. The ability to create and consume services in real time was the primary benefit of this innovation. Recently, the Internet of Things (IoT) has promised to provide the same benefit through its cutting-edge technologies, allowing for an improved user experience by adjusting the physical space in which the user performs their tasks. The Internet of Things (IoT) provides a wide range of benefits in industries as varied as medicine, commerce, transportation, safety, agriculture, the built environment, and the natural environment [17][18]. The Internet of Things (IoT) came into being [19], has experienced explosive growth, and is now firmly entrenched in many people's daily lives and places of business. Since its inception, the IoT has been subject to constant development and change, making it hard to pin down. However, it could be viewed as a system wherein digital and analogue devices and computer systems are connected and assigned unique identifiers (UIDs) so that these systems and devices can automatically share information. Usually, this involves a human communicating with a central device or app, such as a smartphone, which then communicates with other devices on the edge of the Internet of Things. If necessary, the peripheral devices could carry out the task at hand and relay the results to the central device or app, where the user could view them. The IoT concept has improved the world by allowing for more device connectivity that is both open and secure, scalable, private, and compatible with a wide variety of other systems [20]. The IoT has many potentials uses in resource management, spanning many fields and industries. The IoT has completely altered the processes of resource management and optimization thanks to its capacity to link and communicate with a vast array of devices and sensors. Consider some of the following IoT resource allocation applications and Figure 2 shows the architecture for this as given below [21].

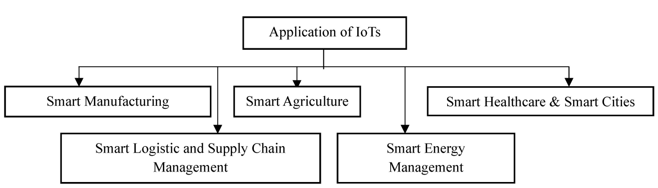


Figure 2. Application of IoTs [21]

1) **Smart Manufacturing:** Optimizing production and predictive maintenance with IoT technology transforms the industry. Using real-time IoT sensors, equipment failures could be predicted for proactive maintenance. A predictive approach reduces downtime and optimizes maintenance resource allocation to ensure continuous operation [22].
2) **Smart Logistic and Supply Chain Management:** Precision farming uses IoT sensors to monitor soil quality, moisture, and crop health, allowing farmers to use water and fertilizers effectively and optimize agricultural output. IoT-enabled livestock monitoring tracks animal health and location, allowing farmers to tailor food and medication to individual animals [23].
3) **Smart Agriculture:** The use of IoT sensors to monitor soil quality, moisture levels, and crop health allows farmers to optimize agricultural output by allocating water and fertilizers precisely. IoT-enabled livestock monitoring tracks animal health and location, allowing farmers to tailor food and medication distribution [24].
4) **Smart Energy Management:** Energy management in utilities and homes is transformed by IoT devices. These devices allow utilities to efficiently allocate energy resources during peak periods by adjusting usage in real-time, reducing grid strain. Smart homes use IoT-enabled devices to regulate heating, cooling, and lighting based on occupancy and user preferences to save energy. This smart allocation saves a lot of energy, making residential spaces more sustainable and cost-effective [25].
5) **Smart Healthcare & Smart Cities:** In smart healthcare, IoT tracks hospital assets to efficiently allocate medical equipment across departments and ensure resource availability. IoT devices also monitor patients in real-time, helping healthcare providers allocate staff and resources, especially in critical care. Waste management IoT-enabled smart bins notifies collection services when full, streamlining resource allocation, reducing costs, and improving cleanliness [26].

There are many problems remaining to resolve in this field. The main problem in optimizing resource allocation in IoT for improved inventory management revolves around finding efficient ways to utilize IoT technologies to optimize inventory tracking, monitoring, and management processes. This includes addressing challenges such as real-time data collection, analysis, and decision-making to minimize stockouts, overstocking, and operational inefficiencies. Additionally, it involves exploring how to allocate resources effectively within the IoT framework to enhance inventory visibility, accuracy, and responsiveness while considering factors like cost-effectiveness, scalability, and sustainability. The research aims to overcome these problems and challenges by enhancing inventory management through efficient resource allocation in IoT systems, minimizing waste and maximizing utilization for improved operational efficiency and cost savings. The research contributes by developing an integrated framework for inventory management in IoT environments, leveraging fuzzy logic and ensemble machine learning for improved accuracy. It assesses scalability and usability across diverse contexts, refining integration for seamless operation. Through impact assessment, it demonstrates tangible enhancements in inventory management outcomes, promoting operational efficiency and cost reduction. The objectives of this research are as follows:

1) To develop an integrated framework that seamlessly integrates real-time inventory monitoring, condition monitoring, data analytics, demand forecasting, and predictive analytics to optimize resource allocation in IoT-enabled inventory management systems.
2) To enhance the accuracy and efficiency of resource allocation decisions, apply fuzzy logic and ensemble machine learning for condition monitoring and demand forecasting.
3) To evaluate the scalability and generalizability of the proposed framework across diverse inventory contexts, providing insights into its applicability in various operational settings.
4) To demonstrate tangible improvements in inventory management, contributing to operational efficiency and cost reduction.

The remaining parts of this research are structured as described below. Previous research is analyzed and discussed in Section 2. In Section 3, the suggested framework is assessed, and its implications are examined. In the next part (section 4), the findings are reviewed, and a brief explanation is also provided for greater comprehension. The study is ended in Section 5, which includes some thoughts on potential future work and the conclusion of the work.

2. Literature of Review

A review of the literature reveals that many authors have attempted this method and published their results.

Ibrahim et al. (2024) [27] designed a method for scheduling packets and allocating resources in 6G networks that were based on the fishnet technique. The author theoretically improved device connection in a 6G-IoT scenario by building a network based on the Sierpinski Triangle. Analysis showed that Fishnet6G performs better than other methods on these measures, proving that it successfully tackles the issues with 6G-IoT networks.

Tan et al. (2024) [28] proposed the inventory management process which is modelled using a nonlinear programming approach that relies on demand variations. The efficient system for managing inventory was implemented via the use of a multi-objective grey wolf optimization (MOGWO) approach, which minimizes storage space requirements while optimizing profit.

Shuaib et al. (2023) [29] proposed a comprehensive approach, dubbed dynamic energy-efficient load balancing (DEELB), to address all of these IoT resource allocation issues. With a decrease of 30.17 % in packet loss ratio analysis and a decrease of 10.352% in delay charges, the simulation results showed that the proposed method is an effective resource allocation approach for fog load balancing.

Fang et al. (2022) [30] addressed the stockout issue, and the team suggested introducing a Hub Vendor Management Inventory (VMI) system. As a result of this study's findings and contributions, inventory management operations had been improved, the total execution time and cost have been cut, response times have been cut for the customer's benefit, and system performance efficiency has been raised.

Han et al. (2022) [31] proposed a case where Vegetation Sampling Protocols (VSPs) hire the Metaverse platform to collect this information from a network of IoT devices. Motivated by their self-interest, device owners actively choose a VSP. In the hybrid evolutionary dynamics, populations of owners of various devices could use various revision protocols to adapt their tactics to changing conditions. Extensive simulations show that using a hybrid protocol could result in evolutionary stable states.

Liang et al. (2021) [32] suggested a Deep Q-Network (DQN) based scheme to optimize bandwidth utilization and power consumption in an Industrial Internet of Things (IIoT) environment. To develop a DQN model that combines two DNNs with a Q-learning model. The scheme outperformed other representative schemes in terms of both bandwidth utilization and energy efficiency, as shown by experimental results.

Tianqing et al. (2021) [33] introduced a new approach to resource allocation known as concurrent federated reinforcement learning. Taking advantage of federated learning's safeguards and reinforcement learning's prowess in solving complex problems, the scheme also incorporates concurrency in the form of joint decision-making to ensure that the system-wide resource allocation strategies are optimal. Experimental results demonstrate state-of-the-art performance in terms of system-wide utility, completion of tasks speed, and utilization of resources.

Ran (2021) [34] constructed a system for managing inventories using cloud-based collaborative computing. The genetic algorithm was used as a benchmark to verify that the system described here really works. The experimental findings show that the weighted average of eigenvalues and fitting prediction approach presented here has the best fitting effect and the least error in the demand forecast of machine spare parts, with a minimum error of just 2.2% after fitting.

Deng and Yongji (2021) [35] used deep learning's long short-term memory (LSTM) theory to develop a deep inventory management (DIM) solution for this model. The testing findings revealed that DIM's mean inventory demand forecast accuracy surpasses 80%, reducing inventory cost by 25% when compared to other state-of-the-art approaches and detecting anomalous inventory activities quickly.

Mashhadi et al. (2020) [36] presented that IoT-enabled manufacturing equipment could provide real-time data that could be used by the Additive Manufacturing (AM) cloud to automatically manage manufacturing resources. Extensive simulations confirmed that the suggested neural network auctions could find a better AM Cloud utility than existing auction schemes.

He et al. (2020) [37] explained that blockchains were ideally suited for edge centric IoT scenarios and how the blockchains solved the security and privacy problems that arise when using edge computing to power IoT. The paper presented simulation results that demonstrate the efficiency of the proposed edge computing resource allocation scheme.

Ren et al. (2020) [38] considered the optimal distribution of resources for an Ultra-reliable low-latency communications (URLLC) system that supports mission-critical Internet of Things (IoT) connectivity. The writers seek a URLLC-compliant, secure, mission-critical IoT network of communication to use in the event that an access point attempts to eavesdrop on devices sending out safety-critical communications. In simulations, the suggested approach demonstrates fast convergence and outperforms the current benchmark algorithm.

Na et al. (2020) [39] introduced joint optimization of Unmanned Aerial Vehicle (UAV) trajectory, subcarrier collection, subcarrier power, and sub-slot distribution aim to maximize the minimum feasible rate between all uplink nodes throughout the constraint of the feasible total rate of all downlinks the nodes within each time slot. The proposed alternate iterative algorithm converges well. The proposed scheme outperformed conventional resource allocation techniques because it raises both the average and total rates that could be achieved by a network of nodes.

Choksi et al. (2019) [40] introduced a method of allocating resources that considers multiple objectives, each of which was subject to its unique constraints. The authors also suggested a parameter-driven algorithm for allocating resources. In the event of resource overuse, the proposed algorithm first employed multi-objective theory for allocation before switching to a priority-based scheduling approach. The authors evaluated the methods against those already in use in the literature. The simulation results show that the methods successfully allocate and schedule resources.

Table 1 shows comparative summary of the related work.

TABLE I. Table 1. Comparative Summary of Related Work

Authors and Years	Techniques	Results	Strength	Weakness
Ibrahim et al. (2024) [27]	Fishnet	Findings demonstrates that Fishnet6G outperforms existing approaches across these metrics, showcasing its effectiveness in addressing the challenges of 6G-IoT networks.	Provides a structured approach to problem-solving.	Diagrams could become complex with many contributing factors.
Tan et al. (2024) [28]	MOGWO	The effective inventory management system is realized using a multi-objective grey wolf optimization (MOGWO) method, reducing storage space while maximizing profit.	Efficiently finds solutions for multiple objectives.	Convergence speed could vary based on problem complexity.
Shuaib et al. (2023) [29]	DEELB	With a decrease of 30.17% in packet loss ratio analysis and a decrease of 10.352% in delay charges, the simulation results showed that the proposed method is an effective resource allocation approach for fog load balancing.	Efficient resource allocation	Complexity
Fang et al. (2022) [30]	VMI System	Findings show that the inventory management operations have been improved, the total execution time and cost have been cut, response times have been cut for the customer's benefit, and system performance efficiency has been raised.	Real-time inventory tracking	Data integration
Han et al., (2022) [31]	VSPs	The findings indicate that having access to comprehensive information about all payoffs results in better strategy adaptation than relying on pairwise imitation, where only the opponent's payoff is considered.	Scalability	Centralized control

Continued on next page

TABLE I – continued from previous page

Authors and Years	Techniques	Results	Strength	Weakness
Liang et al., (2021) [32]	DQN	The scheme outperforms other representative schemes in terms of both bandwidth utilization and energy efficiency, as shown by experimental results.	Adaptability	Training complexity
Tianqing et al. (2021) [33]	Concurrent federated reinforcement learning	Experimental results demonstrate state-of-the-art performance in terms of system-wide utility, completion of tasks speed, and utilization of resources.	Distributed learning	Communication overhead
Ran (2021) [34]	Cloud-based collaborative computing	The experimental results reveal that the weighted average of eigenvalues and fitting prediction technique has the best fitting effect and the lowest demand forecast error for machine spare parts, at 2.2% after fitting.	Resource pooling	Latency
Deng and Yongji (2021) [35]	LSTM	The testing findings reveal that DIM's mean inventory demand forecast accuracy surpasses 80%, reducing inventory cost by 25%.	Temporal sequence modeling	Resource-intensive
Mashhadi et al. (2020) [36]	AM Cloud	Extensive simulations confirmed that the suggested neural network auctions could find a better AM Cloud utility than existing auction schemes.	Adaptive resource management	Dependency on cloud infrastructure
He et al. (2020) [37]	Edge centric IoT	The paper presented simulation results that demonstrate the efficiency of the proposed edge computing resource allocation scheme.	Reduced latency	Limited processing power
Ren et al. (2020) [38]	URLLC	The proposed algorithm has been shown to converge quickly in simulations, and it outperforms state-of-the-art benchmark algorithms.	Ultra-reliable low-latency communication	Implementation challenges

Continued on next page

TABLE I – continued from previous page

Authors and Years	**Techniques**	**Results**	**Strength**	**Weakness**
Na et al. (2020) [39]	Alternate iterative algorithm	The proposed scheme outperforms conventional resource allocation techniques because it raises both the average and total rates that could be achieved by a network of nodes.	Convergence speed	Sensitivity to initial conditions
Choksi et al. (2019) [40]	Parameter-driven algorithm	The simulation results show that the methods successfully allocate and schedule resources.	Flexibility in optimization	Parameter tuning complexity

3. Research Methodology

Resource allocation in inventory management could be improved using sensors. Using the IoT as a lens, this study examines the unique features of business operations throughout the supply chain. To optimize inventory-wide resource allocation, a fuzzy decision model is developed to offer a decision theory for the nodes of the inventory. The proliferation of IoT has resulted in several streams of real-time data and a substantial strengthening of ties between businesses throughout the supply chain. By developing a six-point fuzzy decision-making model, businesses could boost their resource allocation's productivity and bottom line. Decision-making model to enhance inventory node choice procedures. Models for the most efficient distribution of resources might vary widely amongst providers. To enhance businesses' profit-transformation capabilities and gain managerial choices for cloud platforms, a fuzzy decision-making model is established to pinpoint the inventory decision-making point that optimizes resource allocation within a given enterprise's operational capacity. It's like having a road map in the head.

A. Techniques Used

This section gives a summary of all the techniques that are used in this work.

- **Wireless Sensors Network** WSN is a common type of underlying network technology. WSNs are made up of several microsensor nodes that have minimal communication, storage capabilities, and processing [41]. The linked nodes could interact with one another via any channel, either directly or through an established protocol. Due to its format-free architecture, wireless networks might support many independent nodes that are linked together in various ways. Since the network's topology is flexible, any node in the configuration might be added or withdrawn without impacting the rest of the network. In contrast to passive topologies, WSNs are actively self-organizing. Because WSN networking does not need the use of wires, it could be used in settings like houses and offices where the establishment of a network would otherwise be prohibitively expensive. The WSN relies on radio communication methods, and so do its administrators. Protecting sensitive information is a top priority in many different industries and maximizing the efficiency of wireless sensor networks (WSNs) relies heavily on node and network energy efficiency [42]. Because of their versatility, sensor nodes could be used in many contexts. These characteristics provide a potential approach to detecting tasks like power, communication, and processing, and these characteristics could be deployed quickly [43]. Applications need several levels of management, monitoring, and tracking because of the diverse nature of networks. The architecture of WSN for inventory management is shown in Figure 3.

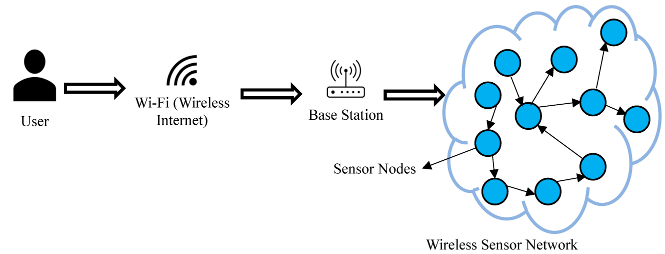


Figure 3. The architecture of WSN for inventory management [44].

- **Fuzzy Logic** Fuzzy logic is a structured approach to trade with data that is difficult to define. A more specific definition of fuzzy logic is a logical system for reasoning under uncertainty that takes a broad view of classical two-valued logic (or Boolean logic). Fuzzy logic encompasses a wide range of concepts and skills that use fuzzy sets, which are programs with fuzzily defined borders. Fuzzy logic enables the definition of intermediate values between the two conventional evaluations of evaluations. In the context of fuzzy expert systems, fuzzy logic is a generalization of traditional (Boolean) reasoning that has been expanded to deal with the theory of limited truth—truth rates that fall somewhere between totally true and false. A fuzzifier (or fuzzification) is one of the f components of a fuzzy expert system (or Defuzzification). Fuzzy logic has an attractive way to deal with the real world rather than trying to describe how things are. The subsequent Figure 4 signifies the block diagram of the Fuzzy logic system.

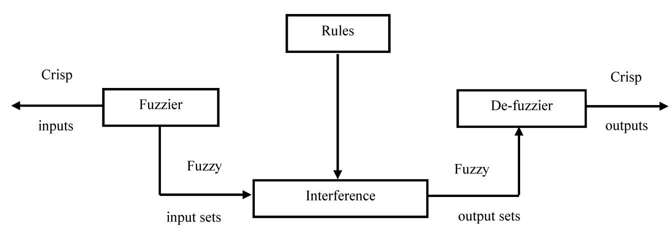


Figure 4. Architecture of Fuzzy Logics [45].

- **Fuzzy Control Rules**
  The fuzzy control rule could be used to describe the level of expertise possessed by a professional in a related field. Once feedback and input are considered when using closed-loop method control, the fuzzy rule could be described as a series of IF-THEN statements that determine what action must be taken in each given situation. Fuzzy rules are governed by a set of rules that are developed based on human perception or knowledge and, hence, are context dependent. Linguistic and fuzzy set parameters are used to define the relationship between the "if" and "then" halves of a fuzzy IF-THEN rule. The IF section might be employed to gather amorphous conditions, and the THEN section could be used to produce a result with

a continuously shifting meaning. This IF-THEN rule is frequently used in the fuzzy interpretation method to determine how well the incoming data meets the rule's condition.

- **Fuzzy Mapping Rules**
  The output-input mapping provided by fuzzy mapping rules makes use of language-specific factors to maximize efficiency. The substance of a fuzzy mapping rule is a diagram of fuzzy, which depicts the connection between the fuzzy output and input. A link between output and input in real-world products could be difficult to find, and even when one is found, the relationship between them could be confusing. In certain circumstances, it makes sense to use fuzzy mapping rules. Like how humans make use of insight and intuition, a series of fuzzy mapping rules might be used to evaluate the entire function rather than relying on a single fuzzy rule mapping. To illustrate the development of fuzzy rule mappings using AC, consider the following case: if the temperature is low, the heater motor must be cranked quickly. Rules need to be defined differently depending on the input temperatures. There are several dimensions to the input variables in most real-world functions. A common example of an input is the difference between the current temperature and the AC rate of temperature variation. Multiple inputs should be considered while computing the outcome of the fuzzy control rules. If-THEN rules are related to temperature inputs that change at a different rate. Every row and every column contain a 3D variable known as control output, which is related to the THEN component of IF-THEN logic. The heater's speed must be fast to swiftly boost its temperature if the present temperature and temperature change rate are low. This is shown by the IF-THEN rule, which states that rapid production is required under conditions of low temperature and low rate of change. Several further rules adhere to a similar manner, which is remarkably near to the intuition of a human. This air conditioner model generates a complete of 9 rules. For functions requiring superior power accuracy, input and output should be separated into smaller portions, and further fuzzy rules should be employed.

B. Dataset

The dataset used in this research comprises primary data collected from multiple industrial companies across various cities. It includes several key parameters such as location, humidity levels, stock availability, stock replacements, stock mapping, availability status, and temperature recorded on different dates ranging from September 13, 2022, to January 1, 2023. This dataset provides comprehensive insights into inventory management dynamics and environmental conditions within industrial settings over a specific time, enabling detailed analysis and informed decision-making for operational optimization and resource allocation strategies.
A short description of the dataset is given below in Table 2.

Date	Stock Mapping	Availability	Temperature	Location	Humidity	Availability Stock	Replacement
14/11/2022	574	In Stock	10.750323	Sri Ganganagar	43.751466	1	0
14/11/2022	710	In Stock	14.186138	Phusro	35.124759	1	0
21/06/2023	747	In Stock	27.714775	Amroha	31.589134	1	0
05/07/2023	107	In Stock	16.559139	Bhagalpur	55.267764	1	0
29/09/2022	850	In Stock	26.837352	Miryalaguda	65.800981	1	0
……	……	……	……	…..	…..	……	……
……	……	……	……	…..	…..	……	……
12/10/2022	773	In Stock	30.234488	Madhyam-gram	61.355038	1	1
09/05/2023	424	Out of Stock	23.624181	Anantapur	67.637464	0	1
01/11/2022	780	In Stock	36.344117	Chandigarh	70.321105	1	1
22/05/2023	368	In Stock	11.346887	Akola	49.537306	1	0
12/10/2022	666	Out of Stock	24.861072	Saharsa	56.221820	0	0

TABLE II. Long Table Example

Component	Specification
IOT devices	Various sensors (e.g., temperature, humidity) connected via MQTT or HTTP protocols
Edge devices	Raspberry Pi 4B with 4GB RAM, running Raspbian OS
Cloud Platform	AWS IoT Core for data ingestion and device management
Data Storage	Amazon S3 for scalable and durable object storage
Data Processing	Python 3.8 with pandas, numpy for data manipulation and analysis
Machine Learning	TensorFlow or PyTorch for developing predictive models
Communication Protocol	MQTT (Message Queuing Telemetry Transport) for efficient device communication
Visualization Tools	Matplotlib, Plotly for data visualization and dashboard creation
Analytics & Monitoring	Elasticsearch, Kibana for real-time analytics and monitoring
Security	SSL/TLS for secure communication between devices and the cloud

C. Tool Used

Python serves as a powerful tool for researching and implementing strategies aimed at optimizing resource allocation in IoT systems for improved inventory management. Python's extensive libraries for data analysis and machine learning, such as pandas, numpy, and scikit-learn, facilitate efficient data processing, modelling, and evaluation. For IoT applications, Python's flexibility allows seamless integration with sensor data streams and cloud platforms, enabling real-time analytics and decision-making. Python's simplicity and readability further enhance collaboration and code reproducibility in research projects focused on enhancing resource allocation efficiency within IoT-driven inventory management systems. This system configuration leverages Python along with appropriate hardware and cloud infrastructure to enable effective resource allocation optimization within IoT-based inventory management systems. The integration of IoT devices, edge computing, cloud services, and data analytics tools in this setup provides a scalable and robust framework for research and practical implementation. Table 3 shows system configuration for implementing the research.

D. Proposed Methodology

The following is a detailed explanation of each approach used in the proposed methodology, along with a flowchart depicting the current state of the methodology in Figure 5.

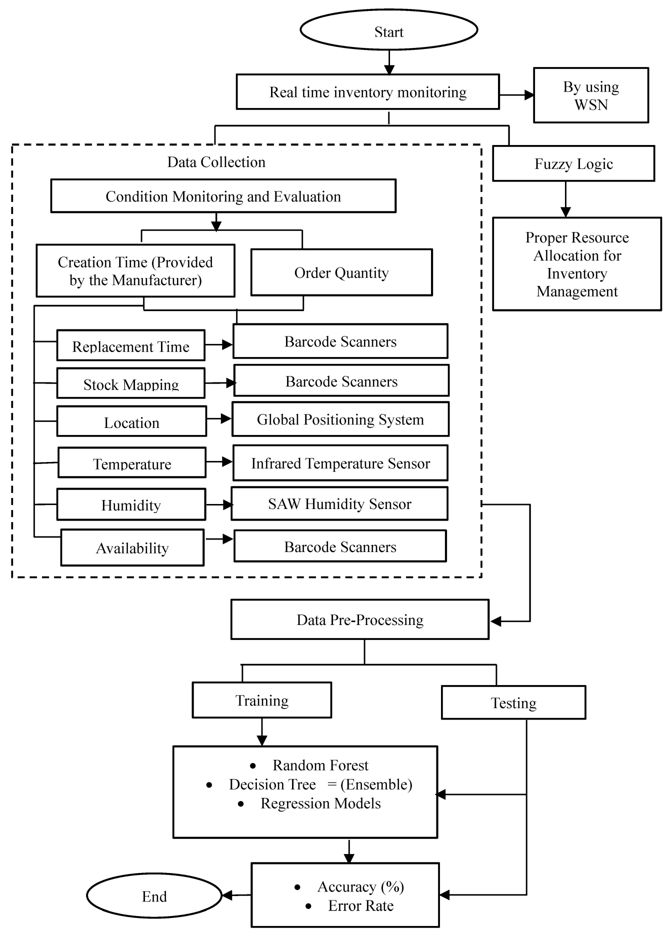


Figure 5. Proposed Methodology Flow diagram.

Step 1:

Real-Time Inventory Monitoring: Sensors could be deployed to monitor inventory levels in real-time. Sensors could be placed on storage shelves, racks, or containers to track the quantity of goods at any given time. This information enables better resource allocation by providing accurate insights into inventory availability and preventing stockouts or overstocking by using WSN, which allows for constant and precise data gathering, inventory monitoring, management, and so on.

Step 2:

Condition Monitoring: Sensors could monitor environmental conditions such as temperature, humidity, and light exposure. This is particularly useful for perishable or sensitive items. By continuously monitoring these conditions, resources could be allocated appropriately to prevent spoilage, damage, or quality issues, and in parallel, the continuous monitoring and evaluation of the performance of the IoT-enabled inventory management system is initialized by using Fuzzy logic and its Fuzzy Rules. Use these insights to refine the resource allocation strategies, make necessary adjustments, and drive continuous improvement. To design a fuzzy conditioning logic for the given scenario, it could define three fuzzy sets: "Low", "Medium", and "High". The input variable would be the "value" of the item, and the output variable would be the "stock_status" with three linguistic terms: "Out of Stock", "Few Items Left", and "In Stock". It could then define the membership functions and rules as follows:

Membership Functions:

1) Input Variable: Value
   - **Low:** Triangular membership function with a range of (0, 130)
   - **Medium:** Trapezoidal membership function with a range of (130, 150)
   - **High:** Triangular membership function with a range of (150 ∞)
2) Output Variable: stock_status
   - **Out of Stock:** Singleton membership function at 0
   - **Few Items Left:** Triangular membership function with a range of (0, 1)
   - **In Stock:** Singleton membership function at 1

Rules:

1) If the value is Low (value<132), then stock_status is Out of Stock.
2) If the value is Medium (132>=value<=150), then stock_status is Few Items Left.
3) If value is High (value>150), then stock_status is In Stock.

Using these membership functions and rules, the fuzzy inference process could be applied to determine the stock status based on the given value. If the value is less than 130, the output would be "Item is Out of Stock." If the value is between 130 and 150, the output would be "Few Items Left, Need More." If the value is greater than or equal to 150, the output would be "Item is In Stock."

Step 3:

Data Analytics and Optimization by sensor data, when combined with advanced analytics and optimization techniques, could provide valuable insights for resource allocation. Data analysis could identify inventory patterns and optimize reorder points, safety stock levels, and order quantities. Optimization algorithms could also be applied to balance resource allocation across multiple locations or channels, minimizing costs while meeting service-level objectives.

Step 4:

Demand Forecasting and Predictive Analytics: Utilize the collected sensor data along with historical data to enhance demand forecasting accuracy. Apply predictive analytics models to forecast future demand, considering factors such as seasonality, trends, promotions, and external events. These forecasts aid in resource allocation decisions.

Step 5:

After collecting data from the following sensors, the information would be preprocessed by performing data cleaning to handle missing values and outliers. Standardize or normalize the input variables to ensure the variable should have a similar scale.

Step 6:

The results would be evaluated using both training and testing data. After that, utilize machine learning algorithms ensembles, such as regression models, decision trees, random forests, or neural networks, to build predictive models based on the available data. Train these models using historical data and validate their performance using appropriate evaluation metrics. Use the trained models to forecast future demand based on input variables and market conditions.

- **Regression Models (Linear Regression):** In the context of the methodology, linear regression can be represented as:

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \quad (1)$$

  Where: $\hat{y}$ is the predicted value, $x_1, x_2, ..., x_n$ are the input features, and $\beta_0, \beta_1, \beta_2, ..., \beta_n$ are the coefficients.

- **Decision Trees:** By applying conditions to characteristics, a decision tree could produce predictions. It is shown as a tree structure, with each internal node representing a decision that is based on a characteristic and every leaf node representing a measurement of the prediction value.

- **Random Forests:** Random forests enhance prediction accuracy by combining many decision trees. A forest of trees is trained using a randomly selected subset of input attributes and training data. When dealing with regression issues, the final forecast is the average of all the trees' projections.

- **Neural Networks (Feedforward Neural Network):** A feedforward neural network consists of interconnected layers of neurons. In the context of the methodology, the output of a neuron in layer l could be represented as:

$$z_j^l = \sigma\left(\sum_{k=1}^{n^{l-1}} w_{jk}^l a_k^{l-1} + b_j^l\right) \tag{2}$$

Where, z_j^l is the output of neuron j in layer l, σ is the activation function, w_{jk}^l is the weight between neuron k in layer $l{-}1$ and neuron j in layer l, a_k^{l-1} is the output of neuron k in layer $l{-}1$, and b_j^l is the bias of neuron j in layer l.

Step 7:

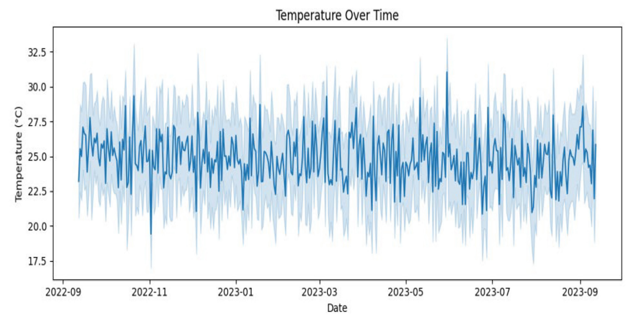
When it comes down to it, the accuracy, and a decreased error rate that ensembles provide are the foundation for both stock management and demand projections.

4. Results and Discussion

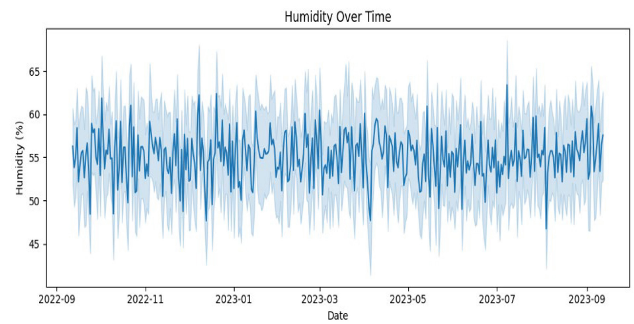
In this section, the study presents and discusses the following key aspects: Firstly, the approach to data representation is outlined, highlighting how data is structured and utilized within the framework. Secondly, evaluation metrics focusing on accuracy, root mean square error, mean square error and mean absolute error are applied to assess performance. Finally, the results derived from these metrics are analyzed and discussed to provide insights into the effectiveness and reliability of the proposed methodology.

A. Data Representation

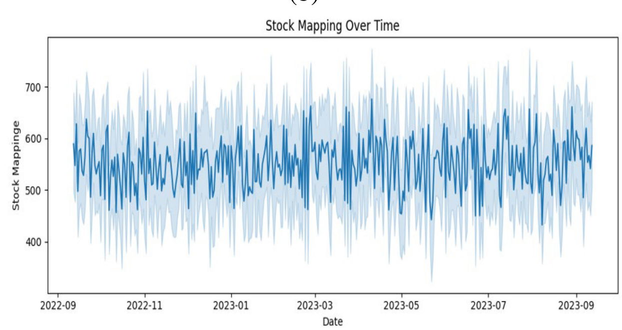
Here, data is visualized, which is collected from various cities with the help of WSN to calculate temperature, humidity, and stock mapping, spanning different dates of allocations where inventory data is located. This data is utilized for testing and training the proposed real-time inventory monitoring system. In this section, data are plotted in the graphs below, which show the temperature, humidity, and mapping of stock at allocated resources in different cities. Figure 6(a) displays the data visualization concerning temperature over time, and it encompasses data collected for both years 2022 and 2023. The minimum temperature recorded is 17.5 degrees Celsius, while the highest temperature reaches 32.5 degrees Celsius. Figure 6(b) illustrates the humidity levels in various cities, represented in percentages, for the years 2022 and 2023. Figure 6(c) displays the stock mapping data for different shops located in the respective cities. (a) displays the data's visualization concerning temperature over time, and it encompasses data collected for both years 2022 and 2023. The minimum temperature recorded is 17.5 degrees Celsius, while the highest temperature reaches 32.5 degrees Celsius. Figure 6(b) illustrates the humidity levels in various cities, represented in percentages, for the years 2022 and 2023. Figure 6(c) displays the stock mapping data for different shops located in the respective cities.



(a)



(b)



(c)

Figure 6. Data Visualization

B. Evaluation Metrics

In this section, evaluation metrics are defined, which are utilized in this study to showcase the results and assess the accuracy of the proposed system. The metrics employed in this study include RMSE, MAE, and MSE.

- **Accuracy**
  Accuracy can be expressed in terms of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) using the following formula:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{3}$$

  Where:
  - True Positives: The number of correctly predicted positive instances (instances the model correctly classified as positive).
  - False Positives: The number of incorrectly predicted positive instances (instances the model incorrectly classified as positive when the numbers are negative).
  - True Negatives: The number of correctly predicted negative instances (instances the model correctly classified as negative).
  - False Negatives: The number of incorrectly predicted negative instances (instances the model incorrectly classified as negative when the numbers are positive).

  Accuracy measures how well the model correctly predicts both positive and negative instances compared to the total number of instances. It provides an overall assessment of the model's performance in terms of classification correctness.

- **Root Mean Squared Error**
  In statistics, the RMSE is a measure of the errors in a set of data points or the precision with which a model makes predictions. RMSE is calculated as follows: take the squared difference between each predicted value (P) and its corresponding actual (true) value (T), calculate the mean (average) of these squared differences, and finally, take the square root of the mean squared differences to get the RMSE.
  Mathematically, RMSE is expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - T_i)^2}{n}} \tag{4}$$

  Where P_i represents the predicted value for the ith data point, T_i represents the true (actual) value for the ith **data** point, and n is the total number of data points.

- **Mean Absolute Error**
  MAE is a statistical metric used to assess the accuracy of a predictive model or to measure the average magnitude of errors in a set of predictions. MAE is calculated as follows: for each data point, calculate the absolute difference between the predicted value (P) and the true value (T), sum up these absolute differences for all data points, and finally, divide the sum by the total number of data points (n) to calculate the MAE.
  Mathematically, MAE is expressed as:

$$MAE = \frac{\sum_{i=1}^{n} |P_i - T_i|}{n} \tag{5}$$

  Where P_i represents the predicted value for the ith data point, T_i represents the true (actual) value for the ith data point, and n is the total number of data points.

- **Mean Squared Error**
  The mean squared error (MSE) is a widely used statistic for gauging the accuracy of a prediction model or for comparing expected and actual values in a dataset. To get the mean squared error (MSE), square each data point's predicted value (P) and the actual value (T), sum all of these squared discrepancies, and then divide by the overall number of data points (n).
  Mathematically, MSE is expressed as:

$$MSE = \frac{\sum_{i=1}^{n} (P_i - T_i)^2}{n} \tag{6}$$

  Where P_i represents the predicted value for the ith data point, T_i represents the true (actual) value for the ith data point, and n is the total number of data points.

C. Results

The results were generated through the application of ensemble techniques and the visualization of confusion matrices. Multiple methods, including Decision Trees, Random Forests, a Regression Model, and an ensemble model that combines Decision Trees, Random Forests, and the Regression Model, are employed to train and classify the data. Notably, the ensemble model demonstrated superior performance, yielding significantly improved accuracy in comparison to the individual methods. This ensemble approach leveraged the strengths of each constituent model, leading to enhanced predictive outcomes and underscoring the efficacy of combining diverse machine-learning techniques to achieve superior results in the classification task. In Figure 7, the confusion matrix for a decision tree model is presented, encompassing key values: TP, FP, TN, and FN, with respective values of 929, 70, 946, and 55. Using these values, the model's accuracy is calculated via the formula of accuracy (Eq. 1), resulting in an accuracy score of 93.75%. This score signifies the model's ability to correctly classify instances, with approximately 93.75% of predictions being accurate. While precision is of the utmost importance, it is also vital to keep the project's objectives in mind. With a Recall of 0.94, a Precision of 0.92, and an F1 Score of 0.92, a thorough evaluation is in line with the needs of the project.

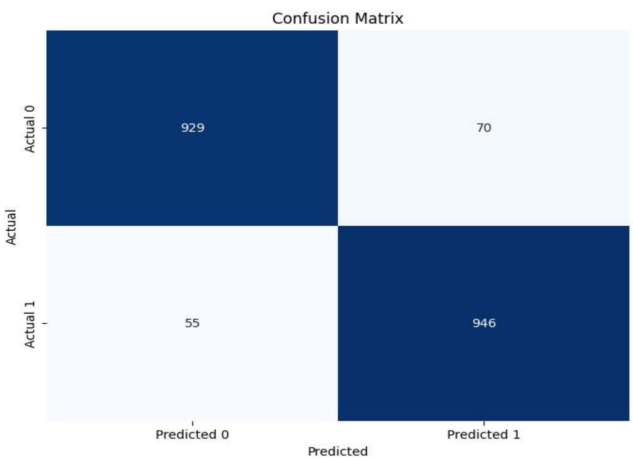


Figure 7. Confusion Matrix for Decision Tree

Figure 8 presents the confusion matrix for a random forest model. This matrix includes crucial values such as TP, FP, TN, and FN, each of which has a value of 942, 57, 934, and 67. The accuracy of the model was determined by using the accuracy formula (Eq. 1) for these data, and the resultant score for accuracy was 93.8%. The model's ability to recognize important examples is highlighted by a recall score of 0.93, and the F1 score of 0.93 indicates a good harmony between precision and recall. An additional indicator of the model's success in correctly identifying positive situations is its precision score of 0.94.

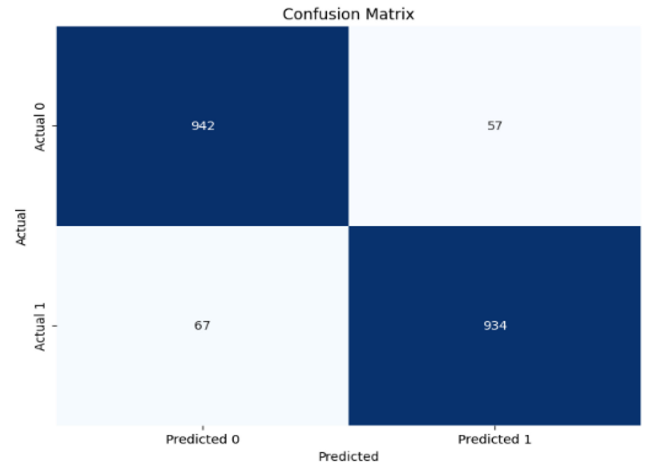


Figure 8. Confusion Matrix for Random Forest

Figure 9 illustrates the confusion matrix associated with a regression model containing essential metrics, including TP, FP, TN, and FN, with respective counts of 942, 57, 934, and 67. To determine the model's performance, applied the accuracy formula (Eq. 3) to these data, yielding an accuracy score of 93.8%. With a 93.8% success rate, the model is quite good at correctly classifying data. To put it another way, the model was successful in making accurate predictions in roughly 93.8% of cases. The levels of recall (0.93), F1 score (0.93), and precision (0.94),

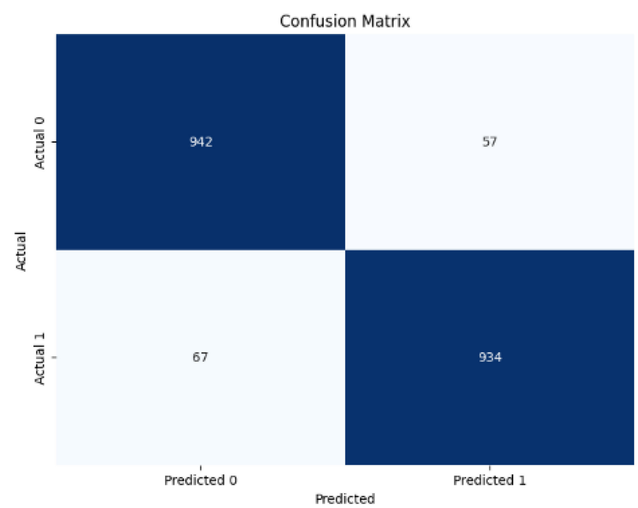


Figure 9. Confusion Matrix for Regression Model

Figure 10 shows the parameter values for several different approaches, such as the Decision Tree, the Rain Forest, and the Regression Model. The confusion matrix for the Decision Tree model shows a remarkable Accuracy of 93.7%, Recall of 0.94, F1 Score of 0.92, and Precision of 0.92. Like the Random Forest model, the Rain Forest model has a high level of accuracy (93.8%) due to its strong Recall (0.93), F1 Score (0.93), and Precision (0.94). The Regression Model achieves similar levels of accuracy (93.8%) with values of 0.93 for Recall, 0.93 for F1 Score, and 0.94 for Precision in the corresponding confusion matrix. Results show that these models perform admirably in classification tasks, with respectable values for important metrics like Recall, F1 Score, and Precision.

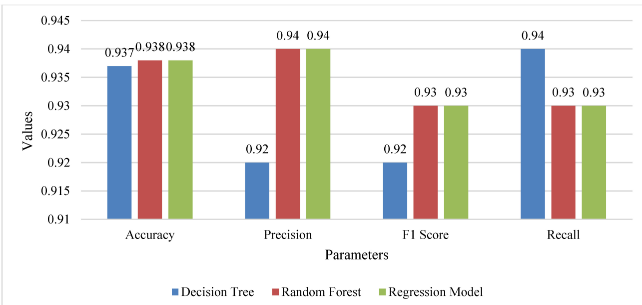


Figure 10. Comparison of Parameter Values for Different Methods

Figure 11 is an illustration of the confusion matrix that relates to the ensemble model (decision tree, random forest, and regression model). This matrix contains crucial metrics such as TP, FP, TN, and FN, and their corresponding counts are 934, 65, 941, and 60, respectively. By putting these numbers into the accuracy formula (Eq. 3), determine that the model has an accuracy of 93.75 %. With a prediction accuracy of almost 93.75%, this score demonstrates the model's ability to properly label events. The remarkable recall (0.93), F1 score (0.93), and precision (0.93) numbers also attest to this success. When compared to using the individual strategies alone, the ensemble model was shown to be much more effective. By making use of the unique features of each model in the ensemble, performance on the classification job was much improved, demonstrating the power of mixing different types of machine learning.

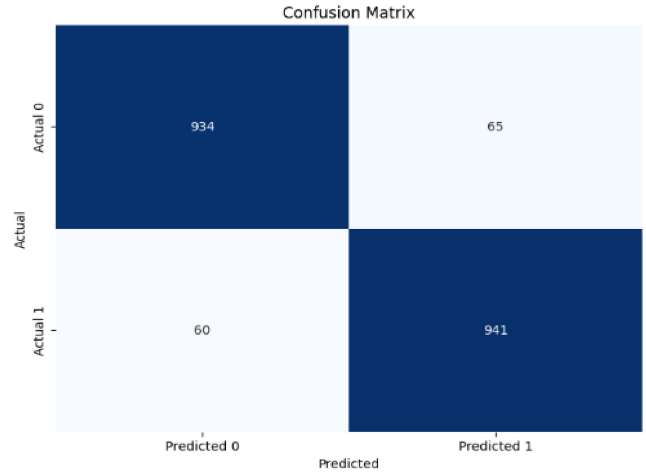


Figure 11. Confusion Matrix for Ensemble Model

Following the computation of these results further assessed the model's performance by calculating error rates, specifically utilizing RMSE, MAE, and MSE. These error metrics were determined using the formulations specified in Eq. 4, Eq. 5, and Eq. 6, respectively. The resulting values for RMSE, MAE, and MSE are presented in Table 4, offering a comprehensive overview of the model's predictive accuracy and deviation from actual values. Additionally, Figure 12 graphically illustrates these error metrics, providing a visual representation of how well the model aligns with the observed data, thus facilitating a deeper understanding of its overall performance.

Parameters	Values
RMSE	0.25
MSE	0.625
MAE	0.625
Accuracy	0.937
Precision	0.93
Recall	0.93
F1-Score	0.93

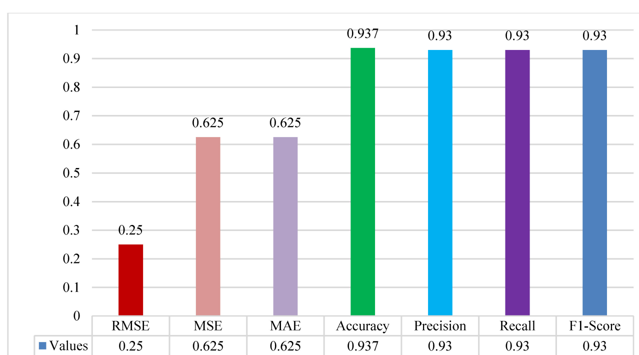


Figure 12. Error Values

5. Conclusion and Future Work

Methods for improving inventory management through optimal use of IoT resources are the focus of this research. In this paper, an inventory management system is developed that uses the IoT and WSN to optimize resource allocation. The dataset that is considered for this article is the main dataset, which was collected from various locations. With the assistance of WSN, temperature, humidity, and stock of mapping of the location where data is allocated are calculated. The collected data is preprocessed, and then the preprocessed data is divided into training and testing data. Further comes the time to classify the data and train it with the use of machine learning models such as decision trees, random forests, regression models, and ensemble models (combinations of decision trees, regression models, and random forests). Accuracy, MAE, MSE, and RSME are the metrics used to evaluate the performance of the model. The results of the experiment demonstrate that the values of RMSE, MAE, MSE, and accuracy are correspondingly 0.25, 0.0625, and 0.625. Also, the obtained accuracy of the suggested model is 93.75%. Future work for this research could focus on expanding the IoT-based inventory management system to handle larger and more complex datasets while exploring the integration of real-time supply chain optimization algorithms to further enhance operational efficiency. Further, advancements in sensor technology and data fusion techniques could be leveraged to enhance the quality and granularity of data collected from IoT devices and WSNs. By incorporating additional sensor modalities and optimizing data fusion algorithms, future iterations of the inventory management system could provide more comprehensive insights into inventory status and environmental conditions, leading to more informed resource allocation decisions.

References

[1] X. Li and L. Da Xu, "A review of internet of things—resource allocation," *IEEE Internet of Things Journal*, vol. 8, no. 11, pp. 8657–8666, 2020.

[2] K. Korpela, J. Hallikas, and T. Dahlberg, "Digital supply chain transformation toward blockchain integration," 2017.

[3] L. Da Xu, W. He, and S. Li, "Internet of things in industries: A survey," *IEEE Transactions on industrial informatics*, vol. 10, no. 4, pp. 2233–2243, 2014.

[4] X. Liu and N. Ansari, "Green relay assisted d2d communications with dual batteries in heterogeneous cellular networks for iot," *IEEE Internet of Things Journal*, vol. 4, no. 5, pp. 1707–1715, 2017.

[5] H. Carvalho, L. Silva, and J. Tavares, "Automated planning applied in inventory management," *IFAC Proceedings Volumes*, vol. 46, no. 24, pp. 147–152, 2013.

[6] Y. Mashayekhy, A. Babaei, X.-M. Yuan, and A. Xue, "Impact of internet of things (iot) on inventory management: A literature survey," *Logistics*, vol. 6, no. 2, p. 33, 2022.

[7] V. Mathur, "IoT in Inventory Management: Impact and Benefits — Analytics Steps." [Online]. Available: https://www.analyticssteps.com/blogs/iot-inventory-management-impact-and-benefits

[8] S. Hamadneh, O. Pedersen, M. Alshurideh, B. Al Kurdi, and H. M. Alzoubi, "An investigation of the role of supply chain visibility into the scottish blood supply chain," *J. Legal Ethical & Regul. Isses*, vol. 24, p. 1, 2021.

[9] N. A. Istiqomah, P. F. Sansabilla, D. Himawan, and M. Rifni, "The implementation of barcode on warehouse management system for warehouse efficiency," in *Journal of Physics: Conference Series*, vol. 1573, no. 1. IOP Publishing, 2020, p. 012038.

[10] D. W. Kim, H. Y. Jang, K. W. Kim, Y. Shin, and S. H. Park, "Design characteristics of studies reporting the performance of artificial intelligence algorithms for diagnostic analysis of medical images: results from recently published papers," *Korean journal of radiology*, vol. 20, no. 3, pp. 405–410, 2019.

[11] I. Diemberger, A. Mazzotti, M. Biffi, G. Massaro, C. Martignani, M. Ziacchi, M. L. B. Reggiani, P. Battistini, and G. Boriani, "From lead management to implanted patient management: systematic review and meta-analysis of the last 15 years of experience in lead extraction," *Expert review of medical devices*, vol. 10, no. 4, pp. 551–573, 2013.

[12] L. Zhao, J. Wang, J. Liu, and N. Kato, "Optimal edge resource allocation in iot-based smart cities," *IEEE Network*, vol. 33, no. 2, pp. 30–35, 2019.

[13] Y. Gu, Z. Chang, M. Pan, L. Song, and Z. Han, "Joint radio and computational resource allocation in iot fog computing," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 8, pp. 7475–7484, 2018.

[14] W. Ejaz and M. Ibnkahla, "Multiband spectrum sensing and resource allocation for iot in cognitive 5g networks," *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 150–163, 2017.

[15] Z. Ghanbari, N. Jafari Navimipour, M. Hosseinzadeh, and A. Darwesh, "Resource allocation mechanisms and approaches on the internet of things," *Cluster Computing*, vol. 22, no. 4, pp. 1253–1282, 2019.

[16] S. Ashraf, "A proactive role of iot devices in building smart cities," *Internet of Things and Cyber-Physical Systems*, vol. 1, pp. 8–13, 2021.

[17] A. Medela, B. Cendón, L. González, R. Crespo, and I. Nevares, "Iot multiplatform networking to monitor and control wineries and vineyards," in *2013 Future Network & Mobile Summit*. IEEE, 2013, pp. 1–10.

[18] M. S. Farooq, S. Riaz, A. Abid, T. Umer, and Y. B. Zikria, "Role of iot technology in agriculture: A systematic literature review," *Electronics*, vol. 9, no. 2, p. 319, 2020.

[19] D. Evans, "The internet of things," *How the Next Evolution of the Internet is Changing Everything, Whitepaper, Cisco Internet Business Solutions Group (IBSG)*, vol. 1, pp. 1–12, 2011.

[20] Y. Lu, "Cybersecurity research: A review of current research topics," *Journal of Industrial Integration and Management*, vol. 3, no. 04, p. 1850014, 2018.

[21] C. Sobin, "A survey on architecture, protocols and challenges in iot," *Wireless Personal Communications*, vol. 112, no. 3, pp. 1383–1429, 2020.

[22] J. Wang, Y. Ma, L. Zhang, R. X. Gao, and D. Wu, "Deep learning for smart manufacturing: Methods and applications," *Journal of manufacturing systems*, vol. 48, pp. 144–156, 2018.

[23] E. M. Frazzon, C. M. T. Rodriguez, M. M. Pereira, M. C. Pires, and I. Uhlmann, "Towards supply chain management 4.0," *Brazilian Journal of Operations & Production Management*, vol. 16, no. 2, pp. 180–191, 2019.

[24] G. Sushanth and S. Sujatha, "Iot based smart agriculture system," in *2018 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*. IEEE, 2018, pp. 1–4.

[25] M. Tastan, "Internet of things based smart energy management for smart home," *KSII Transactions on Internet and Information Systems (TIIS)*, vol. 13, no. 6, pp. 2781–2798, 2019.

[26] T. M. Ghazal, M. K. Hasan, M. T. Alshurideh, H. M. Alzoubi, M. Ahmad, S. S. Akbar, B. Al Kurdi, and I. A. Akour, "Iot for smart cities: Machine learning approaches in smart healthcare—a review," *Future Internet*, vol. 13, no. 8, p. 218, 2021.

[27] A. M. Ibrahim, Z. Chen, H. A. Eljailany, G. Yu, A. A. Ipaye, K. A. Abouda, and W. M. Idress, "Advancing 6g iot networks: Willow catkin packet transmission scheduling with ai and bayesian game-theoretic approach-based resource allocation." *Internet of Things*, p. 101119, 2024.

[28] N. D. Tan, H.-S. Kim, L. N. B. Long, D. A. Nguyen, and S.-S. You, "Optimization and inventory management under stochastic demand using metaheuristic algorithm," *Plos one*, vol. 19, no. 1, p. e0286433, 2024.

[29] M. Shuaib, S. Bhatia, S. Alam, R. K. Masih, N. Alqahtani, S. Basheer, and M. S. Alam, "An optimized, dynamic, and efficient load-balancing framework for resource management in the internet of things (iot) environment," *Electronics*, vol. 12, no. 5, p. 1104, 2023.

[30] X. Fang and H. Chen, "Using vendor management inventory system for goods inventory management in iot manufacturing," *Enterprise Information Systems*, vol. 16, no. 7, p. 1885743, 2022.

[31] Y. Han, D. Niyato, C. Leung, C. Miao, and D. I. Kim, "A dynamic resource allocation framework for synchronizing metaverse with iot service and data," in *ICC 2022-IEEE International conference on Communications*. IEEE, 2022, pp. 1196–1201.

[32] F. Liang, W. Yu, X. Liu, D. Griffith, and N. Golmie, "Toward deep q-network-based resource allocation in industrial internet of things," *IEEE Internet of Things Journal*, vol. 9, no. 12, pp. 9138–9150, 2021.

[33] Z. Tianqing, W. Zhou, D. Ye, Z. Cheng, and J. Li, "Resource allocation in iot edge computing via concurrent federated reinforcement learning," *IEEE Internet of Things Journal*, vol. 9, no. 2, pp. 1414–1426, 2021.

[34] H. Ran, "Construction and optimization of inventory management system via cloud-edge collaborative computing in supply chain environment in the internet of things era," *Plos one*, vol. 16, no. 11, p. e0259284, 2021.

[35] C. Deng and Y. Liu, "A deep learning-based inventory management and demand prediction optimization method for anomaly detection," *Wireless Communications and Mobile Computing*, vol. 2021, pp. 1–14, 2021.

[36] F. Mashhadi and S. A. S. Monroy, "Deep learning for optimal resource allocation in iot-enabled additive manufacturing," in *2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*. IEEE, 2020, pp. 1–6.

[37] Y. He, Y. Wang, C. Qiu, Q. Lin, J. Li, and Z. Ming, "Blockchain-based edge computing resource allocation in iot: A deep reinforcement learning approach," *IEEE Internet of Things Journal*, vol. 8, no. 4, pp. 2226–2237, 2020.

[38] H. Ren, C. Pan, Y. Deng, M. Elkashlan, and A. Nallanathan, "Resource allocation for secure urllc in mission-critical iot scenarios," *IEEE Transactions on Communications*, vol. 68, no. 9, pp. 5793–5807, 2020.

[39] Z. Na, M. Zhang, J. Wang, and Z. Gao, "Uav-assisted wireless powered internet of things: Joint trajectory optimization and resource allocation," *Ad Hoc Networks*, vol. 98, p. 102052, 2020.

[40] M. Choksi, M. A. Zaveri *et al.*, "Multiobjective based resource allocation and scheduling for postdisaster management using iot," *Wireless Communications and Mobile Computing*, vol. 2019, 2019.

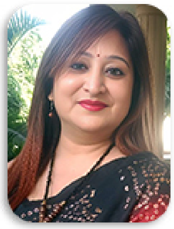
[41] R. E. Mohamed, A. I. Saleh, M. Abdelrazzak, and A. S. Samra, "Survey on wireless sensor network applications and energy efficient routing protocols," *Wireless Personal Communications*, vol. 101, pp. 1019–1055, 2018.

[42] A. Razaque and K. M. Elleithy, "Energy-efficient boarder node medium access control protocol for wireless sensor networks," *Sensors*, vol. 14, no. 3, pp. 5074–5117, 2014.

[43] S. Duobiene, K. Ratautas, R. Trusovas, P. Ragulis, G. Šlekas, R. Simniškis, and G. Račiukaitis, "Development of wireless sensor network for environment monitoring and its implementation using ssail technology," *Sensors*, vol. 22, no. 14, p. 5343, 2022.

[44] T. Mitiku and M. S. Manshahia, "Neuro fuzzy inference approach: a survey," *Int. J. Sci. Res. Sci. Eng. Tech*, vol. 4, pp. 505–519, 2018.

[45] A. M. Nassar, L. Harfuch, L. C. Bachion, and M. R. Moreira, "Biofuels and land-use changes: searching for the top model," *Interface Focus*, vol. 1, no. 2, pp. 224–232, 2011.



Arti Kotru is working as Associate Professor in P.G. Department of Computer Applications, MIET Jammu. Her credentials include acquiring Masters Degree in Physics and Computer Applications from University of Jammu and Indira Gandhi National Open University respectively.She has an experience of over 17 years in teaching and area of interests are in the field of Artificial Intelligence, Internet of Things, Databases and Optimisation Techniques.She is also a member of IAENG and CSTA association.Currently, She is pursuing PhD in Computer Applications from Lovely Professional University in order to expand her horizon of knowledge.

Isha Batra is currently working as Professor in School of Computer Science and Engineering at Lovely Professional University, Punjab. She received her Bachelor of Technology degree from Kurukshetra University in 2008 and completed her Master of Engineering from PEC University of Technology in 2010.She received her PhD degree in Internet of Things from Lovely Professional University, Punjab in 2019. Her research interests include Wireless networks, Sensor Networks, Adhoc Networks and Internet of Things. She has teaching and research experience of 13 years. She has authored more than 55 publications in SCI/Scopus indexed Journals and conferences.