OPTIMIZED WAREHOUSE MANAGEMENT SYSTEM LEVERAGING INDUSTRY 4.0 TECHNOLOGIES

R25-62

BSc (Hons) degree in Information Technology

Specializing in Information Technology

Department of Information Technology

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DECLARATION

I declare that this is my work. This proposal does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any other university or institute of higher learning. To the best of my knowledge and belief, it does not contain any previously published material written by another person except where the acknowledgment is made in the text.

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ABSTRACT

Warehousing can significantly affect supply chain performance, but it can also be a source of inefficiencies, hazards, and poor use of space. This research presents a Comprehensive Warehouse Intelligence Framework that integrates four major modules Route Optimization, Vision- and IoT-Based Fire Detection, Stock Anomaly Detection and Worker Monitoring, and Space Optimization to enable a smart, interconnected warehouse environment.

The Route Optimization module applies Travelling Salesman Problem (TSP) sequencing combined with A* pathfinding to minimize travel distance and avoid physical obstacles in real time. The Vision- and IoT-Based Fire Detection System enhances safety by using YOLO-based computer vision to identify fire and smoke in early stages while employing an IoT subsystem composed of eight LEDs, four buzzers, and four MQ-7 smoke sensors. The LEDs and buzzers provide directional visual and audible alerts up, down, left, and right indicating the location of fire or smoke, even when no smoke is present but flames are detected. The Optimized Warehouse Management System (OWMS) incorporates predictive analytics (ARIMA, Prophet, LSTM) for stock anomaly detection and evaluates worker performance using machine learning classification. The Space Optimization module employs Best-Fit algorithms with 3D visualization to maximize storage utilization and improve space efficiency.

System evaluation using simulation datasets and real-world testing demonstrated improvements in routing efficiency, fire detection accuracy, anomaly forecasting, and spatial utilization. The results collectively show that this integrated framework enhances safety, efficiency, and adaptability supporting the vision of intelligent, Industry 4.0-aligned warehouse management systems.

Keywords: Smart Warehousing, Warehouse Intelligence Framework, Route Optimization, A* Pathfinding, YOLO-based Fire Detection, IoT Alert System, Predictive Analytics (ARIMA, Prophet, LSTM), Worker Monitoring, Space Optimization

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TABLE OF CONTENTS

TABLE OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	**Definition**
AI	Artificial Intelligence
CNN	Convolutional Neural Network – a type of deep learning model commonly used for image classification and detection.
YOLO	You Only Look Once – a real-time object detection algorithm that processes images in a single pass through the network.
YOLOv5	A popular and optimized version of the YOLO model for object detection, known for its speed and accuracy.
OpenCV	Open Source Computer Vision Library – a popular library of programming functions used for real-time computer vision.
Flask	A lightweight Python web framework used to develop web applications and APIs.
RNN	Recurrent Neural Network – a class of neural networks used for sequence prediction, such as video or time-series data.
IoT	nternet of Things – a network of physical devices embedded with sensors, software, and connectivity to collect and exchange data.
Bounding Box	A rectangular box that encloses an object in an image, used in object detection to localize and label targets.

1 List of abbreviations

1. INTRODUCTION

Warehousing has evolved into a crucial strategy within supply chains and has a meaningful influence on many factors such as efficiency, cost, customer service, and agility. As international trade expands, warehouses are transitioning from a passive storage facility role to an active logistic operations hub, where it is necessary to receive, store, pick, pack, and dispatch goods while balancing increasing time and accuracy demands. Furthermore, e-commerce and just-in-time approaches have only increased the demand for smart warehouses that can flexibly and rapidly respond to persistence and complexity in order fulfilment [2], [26]. At the same time, warehouse operators face new challenges including labor shortages, rising operational costs, and safety hazards such as fire risks and workspace congestion [3], [11].

While traditional Warehouse Management Systems (WMS) have evolved to automate key tasks such as stock keeping, order processing, and reporting, most systems remain siloed and functionally specific, lacking a unified intelligence layer [7]. For instance, a system that optimizes order picking rarely integrates fire detection or safety response, and a worker-performance monitoring tool may be dissociated from stock anomaly detection. This absence of integration prevents warehouse operators from managing facilities as holistic, data-driven ecosystems.

The rise of Industry 4.0 technologies including artificial intelligence (AI), computer vision, predictive analytics, and cyber-physical systems offers opportunities to redesign warehouses as intelligent, adaptive, and predictive environments [26], [27]. Dynamic route-optimization methods such as the Travelling Salesman Problem (TSP) and A* pathfinding can reduce travel distance and avoid obstacles in real time [2]. YOLO-based computer vision enables rapid detection of fire and smoke, while predictive analytics techniques such as ARIMA, Prophet, and LSTM improve demand forecasting and anomaly identification [22]. Best-Fit bin-packing algorithms combined with 3D visualization tools help maximize cubic-meter (CBM) capacity and improve transparency of space utilization [3], [4].

To enhance safety, this research also integrates an IoT-based Fire Alert Subsystem consisting of eight LEDs, four buzzers, and four MQ-7 smoke sensors.

These components trigger both visual and audible alerts in directional patterns (up, down, left, right) whenever smoke or fire is detected. Even when only the vision module detects flames without smoke, the IoT unit activates, providing a redundant layer of early warning and situational awareness across the warehouse floor.

To address the identified gaps, this thesis proposes a Comprehensive Warehouse Intelligence Framework that integrates four connected modules Route Optimization, Vision- and IoT-Based Fire Detection, Stock Anomaly Detection with Worker Monitoring, and Space Optimization. Unlike traditional systems with isolated functionalities, this framework provides a holistic, intelligent platform that enhances efficiency, improves safety, and enables predictive decision-making while optimizing spatial utilization. By combining algorithmic optimization, computer vision, IoT, machine learning, and visualization technologies, the proposed framework advances the development of next-generation smart warehouses aligned with Industry 4.0 principles [26], [27].

1.1 Background

Warehousing is a central component of logistics and supply chain management. It connects producers with distributers. Today, a warehouse is no longer thought of as a static storage space, but instead a very active space of operations in which inbound goods are stored, turned around quickly, and successfully sent off to meet ever-increasing demands. The ubiquitous e-commerce era and the rise of just-in-time (JIT) and on-demand delivery have created new expectations for warehouses to act and operate with speed, scalability and accuracy [2, 26].

Despite the improvements, traditional warehouses face many challenges:

- Operational inefficiency: Picking orders takes up to 50% of the warehouse costs, workers take unnecessary steps when planned poorly [2]. Without an effective routing system, productivity is negligible, and labour costs rise.
- Safety concerns: Fire in warehouses can destroy everything. Recent fire detection technologies including smoke detection and heat sensors are flawed

by slow detection times and low sensitivity leading to delays in reaction time [11], [13].

- No predictive capabilities: Most warehouse management systems (WMS) are basically reactive. They maintain inventory records but cannot predict deviations and future demand [22].
- Space, poor use of: Weight and space strategies are ill-defined and without tools to help with space allocation typically lead to clogged aisles and loss of cubic meter capacity (CBM) [3], [4].

Industry 4.0 technologies offer powerful tools to mitigate these challenges. Algorithmic optimization techniques such as the Travelling Salesman Problem (TSP) and A* pathfinding enable efficient routing for pickers, dynamically avoiding moving obstacles like workers and forklifts [2], [7]. Computer vision powered by YOLO models enables early fire and smoke detection, estimation of fire spread direction, and shelf proximity assessment [11], [14]. To enhance this further, an IoT-based alert subsystem consisting of four MQ-7 smoke sensors, eight LEDs, and four buzzers provides real-time directional visual and audible alerts (up, down, left, right) when smoke or fire is detected. Even when no smoke is present, the IoT system activates upon fire detection by the vision module, ensuring immediate awareness and response.

In parallel, Predictive analytics with ARIMA, Prophet, and LSTM to improve demand forecasting and anomaly detection of stock movement enables managers to act before performance drops [22]. At the same time, monitoring workers performance with machine learning classification promotes transparency and healthy evaluation of human factors. Finally, the deployment of Best-Fit bin-packing algorithms and 3D visualization for intelligent place ensuring maximum efficiency and visibity of the warehouse floor lay out [3], [6].

1.2 Literature Survey

In warehouse management literature there is a large body of work dealing with performance issues related to efficiency, safety, predictive intelligence, and spatial efficiency, or warehouse utilization. However, most literature has addressed these areas independently from one another, with limited attention to solutions that cut across space, safety, efficiency, and predictivity where possible. This section will review important contributions in the area of order picking and route optimization, vision-based fire detection, predictive analytics in stock and workforce, space optimization and visualization, and Industry 4.0 in warehousing.

1.2.1 Order Picking and Route Optimization

Picking orders is recognized as the most costly function in warehousing, costing as much as 50% of warehouse costs [2]. And the literature suggests that shortened travel distances are one way to improve productivity. De Koster et al. [2] provided a comprehensive study of modes of order picking strategies with a specific focus on the value of algorithmic optimization. Static routes are more common and inefficient, as they allow the duplicable travel to be made as multiple trips as possible, where heuristic and metaheuristic solutions of Travelling Salesman Problem (TSP) diagonal ordering can simplify travel paths.

Pathfinding such as A* and Dijkstra's are the most well-known path-finding algorithms and are often used in shortest path problems [7]. While in optimal pathing situations like applying TSP ordering, A* has benefited from both efficient routes and adaptability in dynamic scenarios where movement by workers or fork-trucks can affect existing routes with unexpected obstacles. New capabilities in the domain of pathfinding include Ant Colony Optimizations (ACO) and Reinforcement Learning (RL) for adaptive pathing, allowing real-time adaptations to situational variables, however, this presents challenges within warehouse design as every change to warehouse design impacts systems functionally [17]. These works prove that algorithmic optimization is important for efficient operations but show little operational fit with other subsystems of the warehouse such as safety or prediction verification.

1.2.2 Computer Vision and IoT for Fire Detection and Safety

Warehouse fire safety traditionally depends on smoke alarms, sprinklers, and thermal sensors. While effective, these systems are reactive and may trigger only after flames or significant heat are present, leading to delayed responses [11], [13].

The evolution of computer vision techniques has introduced proactive fire detection. Jin et al. [11] demonstrated that deep learning-based fire recognition using video analysis can achieve earlier and more accurate detection compared to conventional sensors. Xu et al. [14] proposed Light-YOLOv5, a lightweight yet efficient model suitable for resource-constrained environments, while Islam and Habib [15] implemented YOLOv5 for real-time video-based detection with high sensitivity.

Recent work extended these models to classify fire size, estimate proximity to shelves, and predict fire spread direction [20], [21]. Studies on shelf monitoring [17], [19] also highlight the importance of spatial context in risk assessment, providing actionable data for prioritizing evacuation or suppression responses.

To complement vision-based methods, this study introduces an IoT-enabled fire alert subsystem composed of four MQ-7 smoke sensors, eight LEDs, and four buzzers. These components generate directional visual and auditory alerts (up, down, left, right) when smoke or fire is detected. Even when flames are visible without smoke, the IoT system activates alongside the vision model, ensuring redundancy and faster awareness. This hybrid Vision + IoT approach bridges a major gap in prior research by coupling deep-learning perception with immediate, localized feedback mechanisms suitable for real-world warehouses.

1.2.3 Predictive Analytics for Stock and Workforce Monitoring

There is also increasing interest in forecasting and anomaly detection within warehouse operations when desirable supply chains operate on a more data-driven basis. While mainstream time series forecasting methods like ARIMA remain prevalent in detecting demand variability and irregularities in stock flow [22], there are also emerging alternatives above mainstream ARIMA including Facebook Prophet as well as the LSTM (Long Short-Term Memory) deep learning models, which are offering superior accuracy in predicting non-linear and seasonal load data patterns [22].

There are multiple aspects to workforce monitoring. For example, Gunasekaran et al. [22] indicated how human factors are important and were quite relevant to the programmatic efficiencies of the supply chain, and explained how modeling on a predictive scale could enhance labor utilization. Recent studies have applied machine learning classification of workers based on their performance levels in areas such as items picked, error counts, and on time task completion rates [24]. For example, categorically gradient boosting and other classifiers offer (roughly) reliable classifications of worker performance into high, average and low bands. Unfortunately, predictive methods often act in isolation from routing, safety and space optimization; therefore, their applicability is limited for systemic considerations.

1.2.4 Space Optimization and Visualization

Efficient space utilization directly impacts warehouse performance and cost management. Singh and Sharma [3] explored bin-packing and visualization algorithms to improve cubic-meter (CBM) usage. Martello and Toth [4] applied knapsack formulations for product placement optimization, while Best-Fit heuristics offered practical solutions balancing computational speed and allocation quality [5].

Beyond optimization, visualization technologies have been increasingly adopted to improve managerial transparency. Bortolini et al. [6] demonstrated how virtual simulation can identify layout inefficiencies such as blocked aisles or poor item grouping, supporting continuous layout improvement. However, most studies in this domain have focused narrowly on storage efficiency, without integrating routing, predictive analytics, or safety considerations into the broader spatial model.

1.2.5 Industry 4.0 and Smart Warehousing

The overall context of these developments is based on Industry 4.0, which highlights the prospects of digitalisation, predictive analytics, and intelligent automation. Waller and Fawcett [26] have identified predictive analytics as a revolution that fundamentally questions supply chain design and decision-making. Hofmann and Rüsch [27] discussed how Industry 4.0 technologies (IoT, Cyber-Physical Systems, Big Data, etc.) will follow on from other developments as the basis for future logistics systems.

In warehousing, Industry 4.0 espouses a holistic approach that combines disparate functions into cohesive, intelligent ecosystems. Study of the individual subsystems has separately continued to advance (routing, equation fire detection, analytics, space utilization, etc.), but research has not progressed to an integrated framework that can encompass the opportunity to think of efficiency, safety, adaptability, and intelligence in one model. In essence, this integrated framework represents the novel contribution of this paper.

1.3 Research Gap

The literature on warehousing indicates steady progress in maximizing single processes, such as routing, safety, inventory forecasting, and space utilization. However, there are observable limitations to research and practice when considered holistically. The subsequent discussion provide the key gaps identified in five thematic themes and the wider perspective of Industry 4.0 integration.

1.3.1 Gaps in Route Optimization

Order picking, historically viewed as the most costly task in warehousing [2]. Routes minimizing travel distances and improving efficiency have been implemented in autonomous systems by algorithms for the Travelling Salesman Problem (TSP) and A* pathfinding [2], [7]. More advanced operations such as Ant Colony Optimization and Reinforcement Learning improve situational adaptability in dynamic environments in real time [17].

Limitation: Still, route optimization models are commonly tested in simulated environments and not adapted for real-time interaction with other warehousing subsystems, finding an ideal path without consideration of interactions with space constraints, worker effectiveness or emergencies such as fire.

1.3.2 Gaps in Fire Detection and Safety

Recent advancements in computer-vision-based fire detection, particularly with YOLO architectures [11], [14], have achieved faster and more accurate recognition than conventional smoke or heat sensors. Some models extend functionality to include fire size estimation and spread prediction [20], [21].

Limitation: Despite these improvements, most fire-detection systems function as standalone safety tools, detached from broader warehouse management operations. They focus on visual identification without offering integrated decision support. Moreover, earlier studies overlook IoT-based, multi-modal alert mechanisms that provide real-time sensory confirmation and immediate directional alerts (e.g., through MQ-7 smoke sensors, LEDs, and buzzers). Integrating computer vision with IoT feedback would create a redundant, context-aware safety layer capable of delivering both digital and physical alerts an aspect largely unexplored in current research.

1.3.3 Gaps in Predictive Analytics for Stock and Workforce Monitoring

In predicting demand variation and detecting irregular stock movements, forecasting and anomaly detection with ARIMA, Prophet, and LSTM showed usefulness [22]. Workforce analytics have been transformed by machine learning classifiers that estimate worker productivity and errors on the job [24].

Limitation: Most predictive approaches are independently implemented that only capture either stock movement or workforce monitoring, but not both. Moreover, those approaches hardly reviewer back to decisions on routing or space utilization, leaving intelligence unconnected across subsystems.

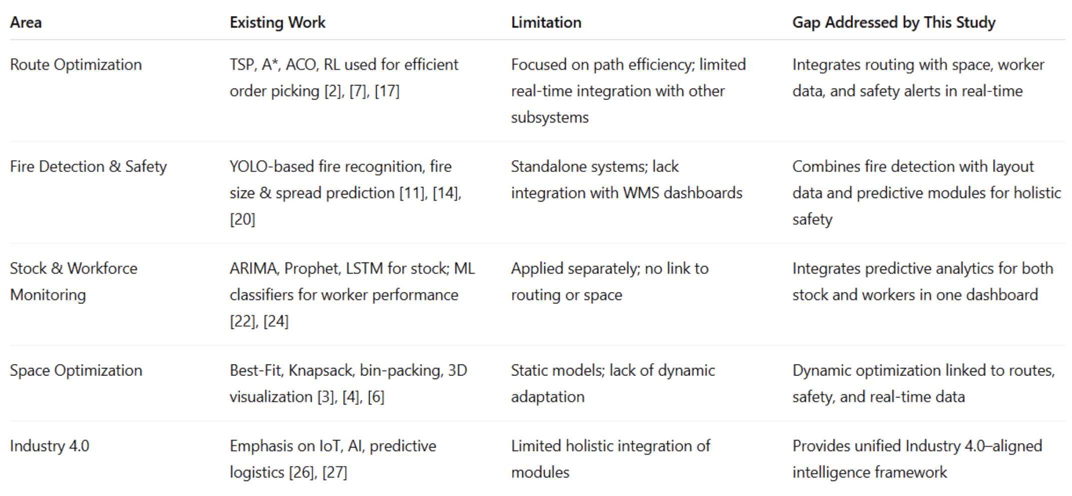
1.3.4 Gaps in Space Optimization and Visualization

Best-Fit heuristics, Knapsack problem formulations, and bin-packing models are established algorithms that have successfully maximized CBM utilization [3], [4], [5]. 3D visualization tools enhance managerial visibility by providing real-time awareness of space utilization [6].

Limitations: These solutions are static, primarily focused on initial warehouse design as opposed to numerous potential and continuous dynamic adjustments occurring through incoming sales orders, logistics routing changes, and safety mitigation considerations. These solutions do not interact, and make decisions in the same context and time frame as predictive analytics and fire detection systems.

1.3.5 Integration and Industry 4.0 Context

Industry 4.0 accentuates the merging of IoT, AI, and cyber-physical systems into integrated logistics networks [26], [27]. Although there are advances in routing, vision, analytics and space in their own right, most frameworks do not combine all of these into a cohesive warehouse intelligence system. Most research also tends to focus on individual optimizations creating a highly fragmented intelligence space, limiting the ability to adapt to actual complexity.



Area	Existing Work	Limitation	Gap Addressed by This Study
Route Optimization	TSP, A*, ACO, RL used for efficient order picking [2], [7], [17]	Focused on path efficiency; limited real-time integration with other subsystems	Integrates routing with space, worker data, and safety alerts in real-time
Fire Detection & Safety	YOLO-based fire recognition, fire size & spread prediction [11], [14], [20]	Standalone systems; lack integration with WMS dashboards	Combines fire detection with layout data and predictive modules for holistic safety
Stock & Workforce Monitoring	ARIMA, Prophet, LSTM for stock; ML classifiers for worker performance [22], [24]	Applied separately; no link to routing or space	Integrates predictive analytics for both stock and workers in one dashboard
Space Optimization	Best-Fit, Knapsack, bin-packing, 3D visualization [3], [4], [6]	Static models; lack of dynamic adaptation	Dynamic optimization linked to routes, safety, and real-time data
Industry 4.0	Emphasis on IoT, AI, predictive logistics [26], [27]	Limited holistic integration of modules	Provides unified Industry 4.0–aligned intelligence framework

Figure 1 Research Gap

1.4 Research Problem

Warehousing has shifted from a passive storage function to a vital supply chain differentiator. With the growth in e-commerce, globalization, and just-in-time delivery processes, warehouses will be pressed to perform to an unprecedented level of accuracy, flexibility, and efficiency [2], [26]. But even with technological advancements, four key issues remain open in the area of route optimization: safety, predictive analytics, and space utilization

The most pressing identified problem is inefficient order picking. The costs of order picking alone may account for almost fifty percent of warehouse costs [2]. Existing navigation solutions that rely on TSP- and A*-based routing still advance travel distance but are highly focused on isolated aspects of the warehouse and fail to account for real-time obstructions, operator performance, and situational awareness of broader systems within the warehouse [7], [17] causing warehouses to suffer from unnecessary travel redundancies, congestion, and the inability to fulfill customers' orders in a timely manner.

Safety is another pressing issue. Fire detection systems have been reactive to date, mostly relying on smoke and heat sensors which act too slow to stop the escalation of a fire. Computer vision has been explored as a viable alternative [11], [14], but existing systems are deployed as separate safety modules. They can detect fire, but they do not connect to warehouse layouts, routing systems, or worker monitoring dashboards to improve situational awareness and operational impact during emergencies.

Further, the lack of predictive intelligence in warehouse systems does not help matters. Although forecasting models like ARIMA, Prophet, and LSTM have been deployed for stock anomaly detection [22], they have not been employed in real-time WMS applications. Similarly, workforce monitoring systems that exist have mainly focused on attendance or counts of tasks completed as KPIs [24]. The fragmented system prevents the manager from connecting stock anomalies with worker performance, negating opportunities for targeted intervention, training, or efficiency improvement.

Space utilization is another unresolved challenge. Warehouses often have cramped aisles, wasted cubic meter (CBM) space, and poor layouts. Best-Fit bin-packing algorithms and 3D visualization tools have been suggested [3], [4], but they are typically only used when designing warehouses, and not for real-time dynamic operations. This doesn't allow for any modifying, to adapt to changes in demand pattern, fire hazard extent, or route degree changes.

The issue, therefore, isn't just the three. The lack of inter-facility connectivity creates unmanaged issues. Modern warehouse technologies that exist are treated as siloed technologies. They focus on one aspect of efficiency, one aspect of safety, or one aspect of prediction. However, they do not provide a level of intelligence that could link-up across the facilities. Thus, allowing facilities to perform in an manner that makes them sustainable as well as adaptable. The governed risk needs to be predictable, the process adaptive, and warehouse off putting are definitely challenging to resolve to meet the variables of the dynamic supply chain.

Thus, the research problem can be stated as follows:

"How can a unified warehouse intelligence framework be designed and implemented to integrate optimization, safety, predictive analytics, and space utilization into a single, scalable system that enhances efficiency, ensures safety, supports predictive decision-making, and aligns with Industry 4.0 standards?"

By addressing this problem, the proposed research aims to fill a critical gap in warehouse management by moving beyond isolated optimizations and delivering a holistic solution that transforms warehouses into intelligent, adaptive, and resilient nodes within modern supply chains

1.5. Objectives

The goal of this mistreatment is to develop and implement a Comprehensive Warehouse Intelligence Framework that combines optimization, safety, predictive analytics, and space utilization in one system. The Comprehensive Warehouse Intelligence Framework will use algorithms, computer vision technology, predictive modeling, and visualization technology to create intelligent, adaptable, and Industry 4.0- compliant warehouse ecosystems. The objectives are divided into two levels: the overall Main Objective and a group of Specific Objectives which provide a more granular breakdown of the research scope into specific deliverables.

1.5.1 Main Objective

The primary objective of this project is:

"To create and validate an integrated warehouse intelligence framework that combines route optimization, vision- and IoT-based fire detection, stock anomaly and worker performance monitoring, and space optimization into a unified, scalable system. The framework aims to deliver enhanced efficiency, safety, and predictive decision-making aligned with the principles of Industry 4.0."

This primary aim recognizes the need for an integrated warehouse solution, moving past isolated solutions that address warehouse efficiency, safety risk, predictive intelligence, and resources utilization independently.

1.5.2 Specific Objectives

To achieve the main objective, the research is structured around the following specific objectives:

1. **Develop a Route Optimization Module**

- Implement **TSP sequencing** and **A*** pathfinding to generate efficient picking routes.
- Ensure adaptability to real-time obstacles, such as moving forklifts or blocked aisles, by simulating dynamic routing within the warehouse environment.

2. **Design a Vision- and IoT-Based Fire Detection and Prevention System**

- Utilize YOLO-based deep learning models for early fire and smoke recognition, fire size classification, and shelf proximity estimation.
- Integrate an IoT alert subsystem consisting of four MQ-7 smoke sensors, eight LEDs, and four buzzers to provide directional visual and audible alerts (up, down, left, right) based on the location of smoke or flames.
- Implement fire spread prediction mechanisms using temporal frame analysis to forecast potential propagation paths, enabling proactive response and evacuation strategies.

3. **Implement a Predictive Analytics Framework for Stock and Worker Monitoring**

- Apply **ARIMA, Prophet, and LSTM** models to forecast stock movements and detect anomalies such as shortages, surpluses, or misplaced items.
- Utilize **machine learning classification** techniques (e.g., Gradient Boosting) to evaluate worker performance based on activity logs, productivity rates, and error counts.
- Integrate stock anomaly insights with worker monitoring to provide managers with actionable intelligence.

4. **Develop Space Optimization and Visualization Module**

- Utilize **Best-Fit bin-packing algorithms** to maximize cubic meter (CBM) utilization in dynamic warehouse environments.
- Save Current Allocated Location and measure free space and allocate new items for that free space.
- Incorporate 3D visualization tools to provide real-time visibility of warehouse layouts, highlighting congestion, underutilized zones, and optimization opportunities.

5. **To combine all modules into one, deployable, real-time vision-based monitoring system**

- Build an integrated **dashboard interface** that combines routing, safety alerts, predictive insights, and space optimization.
- Ensure real-time data synchronization, scalability, and adaptability to Industry 4.0–based warehouse practices.

6. **Evaluate the System Through Experimental Validation**

- Build an integrated **dashboard interface** that combines routing, safety alerts, predictive insights, and space optimization.

- Ensure real-time data synchronization, scalability, and adaptability to Industry 4.0–based warehouse practices.

2. METHODOLOGY

This research adopted a design and implementation-based methodology for the conception and development of a Comprehensive Warehouse Intelligence Framework, integrating four fundamental modules: route optimization, vision- and IoT-based fire detection, stock anomaly detection with worker monitoring, and space optimization.

The development process began with a requirements analysis, identifying key operational challenges common in warehouse environments—such as inefficient order-picking routes, delayed responses due to traditional fire alarm systems, reactive stock anomaly detection, and suboptimal use of warehouse space. Understanding these functional and non-functional requirements guided the design of individual subsystems, which were later integrated into a unified intelligent framework.

The Route Optimization Module implemented the Travelling Salesman Problem (TSP) in combination with A* pathfinding to generate optimal picking routes. This ensured the shortest possible travel distances while maintaining adaptability to dynamic environmental variables such as moving forklifts or temporary obstructions.

The Vision- and IoT-Based Fire Detection Module employed a YOLO-based deep learning model for early identification of fire and smoke, fire size classification, shelf proximity estimation, and prediction of fire spread direction. To enhance safety and responsiveness, an IoT alert subsystem was integrated comprising four MQ-7 smoke sensors, eight LEDs, and four buzzers. This subsystem provided directional visual and audible alerts (up, down, left, right) based on where fire or smoke was detected. Even in cases where the AI detected flames before smoke formation, the IoT module was triggered, creating a redundant, multi-modal alert mechanism for improved situational awareness.

The Stock and Worker Monitoring Module applied predictive analytics techniques specifically ARIMA, Prophet, and LSTM models to forecast stock movement and identify anomalies such as overstocking, shortages, or misplaced inventory. Machine learning classifiers (e.g., Gradient Boosting) were also implemented to evaluate worker performance based on activity logs, productivity, and error rates. Insights from both stock and worker data were combined to provide managers with actionable intelligence for improving overall warehouse efficiency.

The Space Optimization Module utilized Best-Fit bin-packing algorithms to maximize cubic meter (CBM) usage and reduce wasted storage space. Additionally, 3D visualization tools were incorporated to help administrators visualize the warehouse layout in real time, identify congestion, and adjust shelf allocations dynamically for optimal spatial utilization.

All modules were developed using a MERN + Flask architecture, with MongoDB serving as the database and React.js providing the interactive dashboard interface. The final integrated system offered real-time monitoring, predictive analysis, and context-aware decision support, ensuring both analytical insight and operational control within a single platform.

System validation was performed using synthetic simulation datasets and case-based testing under near-real warehouse conditions. Key performance metrics included improvements in route efficiency, anomaly detection accuracy, fire recognition response time, and space utilization. The methodology emphasized modularity, scalability, and flexibility, ensuring that the proposed framework aligns with the academic rigor and practical demands of Industry 4.0–compliant smart warehouse environments.

2.1. System overview

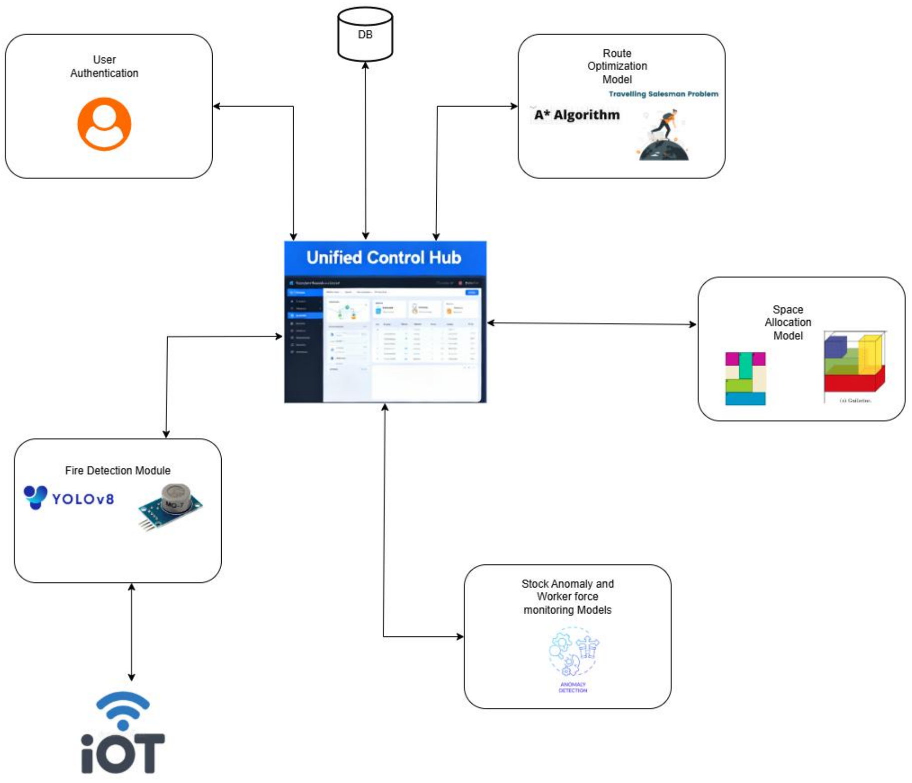


Figure 2 System Overview Diagram

The system architecture illustrates the workflow of the proposed Comprehensive Warehouse Intelligence Framework, which integrates four intelligent modules operating in coordination through a unified dashboard interface. The process begins when authorized users access the system via a secure authentication interface. Once authenticated, users are directed to the main dashboard, which serves as the central control hub for real-time visualization and interaction with all subsystems.

The Route Optimization Module receives order and product-related data, applies Travelling Salesman Problem (TSP) sequencing with A* pathfinding, and generates the most efficient product-picking routes. The system continuously monitors for congestion or obstructions within aisles and dynamically updates routes to ensure uninterrupted workflow and minimized travel time.

The Vision- and IoT-Based Fire Detection Module processes live video feeds through a YOLO-based deep learning model to identify fire or smoke, analyze proximity to shelving units, and predict the potential direction of flame spread. In parallel, the IoT subsystem, consisting of four MQ-7 smoke sensors, eight LEDs, and four buzzers, provides directional visual and audible alerts (up, down, left, right) when smoke or fire is detected. Even in cases where flames are visible without smoke, the LEDs and buzzers activate automatically, ensuring immediate awareness and redundancy. When fire is detected, the system sends alerts to the dashboard and triggers route recalculations to avoid hazardous areas.

The Stock Anomaly and Worker Monitoring Module utilizes ARIMA, Prophet, and LSTM models to analyze stock transaction logs and detect anomalies such as abnormal inflow, outflow, or discrepancies in inventory. Simultaneously, machine learning classifiers evaluate worker productivity using task completion rates, activity logs, and error counts. These analytics are visualized on the dashboard, allowing managers to monitor warehouse performance and workforce efficiency in real time.

The Space Optimization Module applies a Best-Fit bin-packing algorithm and integrates 3D visualization tools to maximize cubic meter (CBM) utilization, minimize congestion, and highlight underused or empty shelf spaces.

All four modules are executed collaboratively on a MERN + Flask stack, where MongoDB handles data storage, Flask serves as the machine learning and IoT integration layer, and React.js provides the interactive dashboard interface. Together, these modules form a unified, intelligent, and adaptive warehouse management framework that enhances efficiency, safety, and decision-making within the context of Industry 4.0.

Component	**Technology / Framework**
Frontend (Dashboard UI)	React
Backend	Express
Database	MongoDB
Computer Vision Library	OpenCV (image processing, contour analysis)

Deep Learning Models	CNNs, YOLOv5 (fire & shelf detection), U-Net / RNN (fire spread prediction)
Frameworks	TensorFlow, PyTorch (for training & inference)
Deployment	Local Server / GPU-supported PC (edge deployment)
Optional Cloud Hosting	AWS / Google Cloud (for scalability)

2 Technologies and frameworks

2.2 Commercialization

The project is extremely commercially viable in the market for warehouse management and supply chain optimization. This project meets a growing appetite for improved efficiency, safety, predictive intelligence, and space utilization in today's warehouses, particularly in relation to Industry 4.0. The proposed framework is a complete, modular, and economical solution that can be implemented with existing infrastructure and minimal hardware investment, rather than utilizing a disjointed system that works on one function at a time. It also relies on open-source technologies, provides real-time AI analytics, and is modular in design, making it both scalable and appealing to a wide spectrum of enterprises.

1. **Target Market:**

The initial target customers include:

- **Warehouses and distribution centers** (e-commerce, retail, logistics, and manufacturing).
- **Third-party logistics providers (3PLs)** seeking scalable solutions.
- **Pharmaceutical and cold storage facilities** requiring high levels of accuracy and safety.
- **Government and defense storage depots** where efficiency and hazard prevention are critical.

- **Medium to large enterprises** with existing CCTV, ERP, or WMS infrastructure that can integrate easily.

2. **Unique Selling Points (USPs):**

- **Integrated Framework**: Combines route optimization, fire detection, anomaly forecasting, and space utilization in one system.
- **Real-Time AI Analytics**: Delivers instant detection, prediction, and adaptive decision-making through deep learning and forecasting models.
- **Modular Design**: Businesses can start with a single module (e.g., route optimization or fire detection) and expand to the full suite.
- **Cost-Effective**: Built on open-source tools, with minimal additional hardware required.
- **Non-Intrusive Deployment**: Integrates with existing WMS, CCTV, and warehouse infrastructure without significant downtime.

3. **Market Entry Strategy:**

- **Pilot Programs**: Offer free or discounted trials in medium-sized warehouses to build trust and gather testimonials.
- **Partnerships**: Collaborate with ERP/WMS vendors, CCTV providers, and fire safety consultants for faster adoption.
- **Online Marketing**: Launch a dedicated website with demos, ROI calculators, and case studies showcasing efficiency gains.
- **Industry Events**: Exhibit at logistics, supply chain, and fire safety expos to increase visibility.
- **Compliance and Certification**: Ensure alignment with fire safety standards, data protection laws, and warehouse operation guidelines to strengthen credibility.

4. **Scalability and Expansion:**

   - **Cross-Domain Applications**: Expand beyond warehouses into **hospitals, schools, airports, and shopping malls** for fire detection and efficiency monitoring.
   - **Multilingual and Regional Customization**: Adapt the system for different markets with localized dashboards and alerts.
   - **Cloud + Edge Deployment**: Offer both on-premises and cloud-hosted solutions depending on client size and budget.
   - **Mobile Integration**: Provide real-time alerts, KPI tracking, and fire hazard notifications via mobile apps for managers on the go

2.3 Testing & Implementation

The implementation and testing of the Comprehensive Warehouse Intelligence Framework was designed to be implemented in multiple stages, utilizing frontend implementation, backend implementation, model & algorithm implementation, and validation/testing. Each stage had the goal to validate that the system was operational, correct, and aligned with all dimensions of efficiency, safety, predictive intelligence, and space utilization.

2.3.1 Frontend Implementation – React (Administrator Panel)

The admin UI is a **React** SPA organized by pages and shared components. It consumes two backends:

- **Flask** – MJPEG video stream (/video) + status JSON (/status).
- **Node/Express** – auth, users, and alert/event logs.

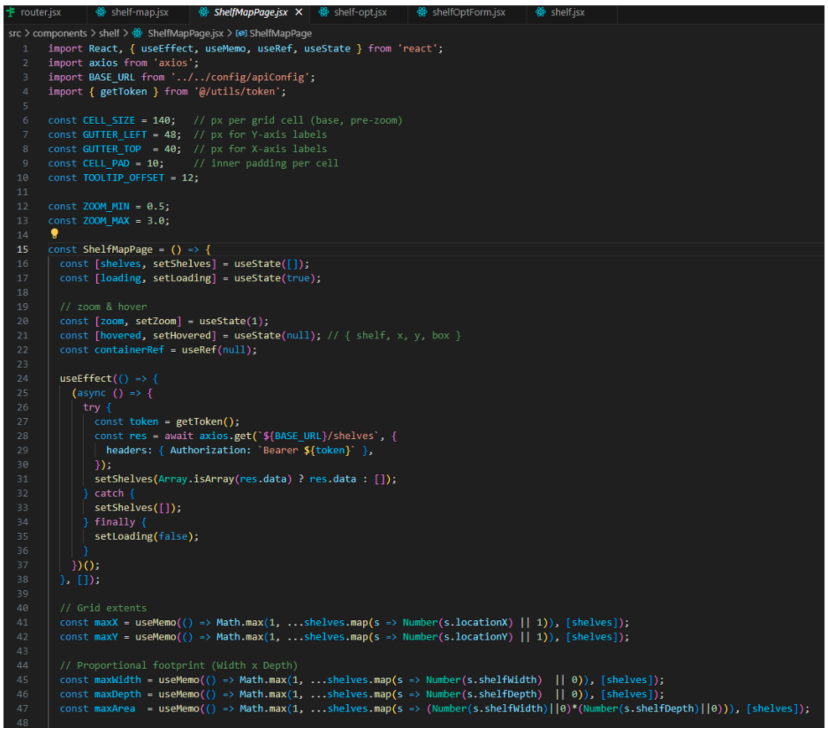
Key pages & components

- **Route Visualization**: Displays optimized routes and updates dynamically when obstacles or fire alerts are detected.
- **Fire Detection Alerts**: Real-time bounding boxes and confidence scores from the YOLO model are overlaid on camera feeds.
- **Stock Forecast Graphs**: Line charts showing actual vs. predicted stock, with anomalies highlighted.
- **Worker Monitoring Panel**: Visualizes worker performance categories (high/average/low).

- **3D Layout Visualization**: Provides a graphical view of CBM utilization and congested areas.

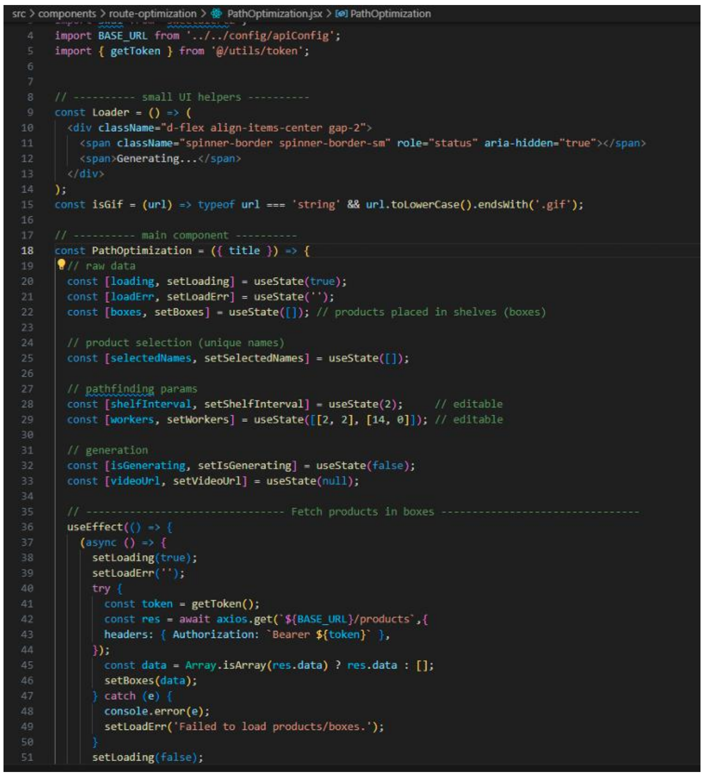
State & libraries

- **React Router** for navigation; **Context** for camera stream; **Axios** for API calls.
- **JWT** stored via **HttpOnly cookies**; role-based route guards.
- **Socket.IO** real-time data transferring.



```
import React, { useEffect, useMemo, useRef, useState } from 'react';
import axios from 'axios';
import BASE_URL from '../../config/apiConfig';
import { getToken } from '@/utils/token';

const CELL_SIZE = 140;   // px per grid cell (base, pre-zoom)
const GUTTER_LEFT = 48;  // px for Y-axis labels
const GUTTER_TOP  = 40;  // px for X-axis labels
const CELL_PAD = 10;     // inner padding per cell
const TOOLTIP_OFFSET = 12;

const ZOOM_MIN = 0.5;
const ZOOM_MAX = 3.0;

const ShelfMapPage = () => {
  const [shelves, setShelves] = useState([]);
  const [loading, setLoading] = useState(true);

  // zoom & hover
  const [zoom, setZoom] = useState(1);
  const [hovered, setHovered] = useState(null); // { shelf, x, y, box }
  const containerRef = useRef(null);

  useEffect(() => {
    (async () => {
      try {
        const token = getToken();
        const res = await axios.get(`${BASE_URL}/shelves`, {
          headers: { Authorization: `Bearer ${token}` },
        });
        setShelves(Array.isArray(res.data) ? res.data : []);
      } catch {
        setShelves([]);
      } finally {
        setLoading(false);
      }
    })();
  }, []);

  // Grid extents
  const maxX = useMemo(() => Math.max(1, ...shelves.map(s => Number(s.locationX) || 1)), [shelves]);
  const maxY = useMemo(() => Math.max(1, ...shelves.map(s => Number(s.locationY) || 1)), [shelves]);

  // Proportional footprint (Width x Depth)
  const maxWidth = useMemo(() => Math.max(1, ...shelves.map(s => Number(s.shelfWidth)  || 0)), [shelves]);
  const maxDepth = useMemo(() => Math.max(1, ...shelves.map(s => Number(s.shelfDepth)  || 0)), [shelves]);
  const maxArea  = useMemo(() => Math.max(1, ...shelves.map(s => (Number(s.shelfWidth)||0)*(Number(s.shelfDepth)||0))), [shelves]);

```

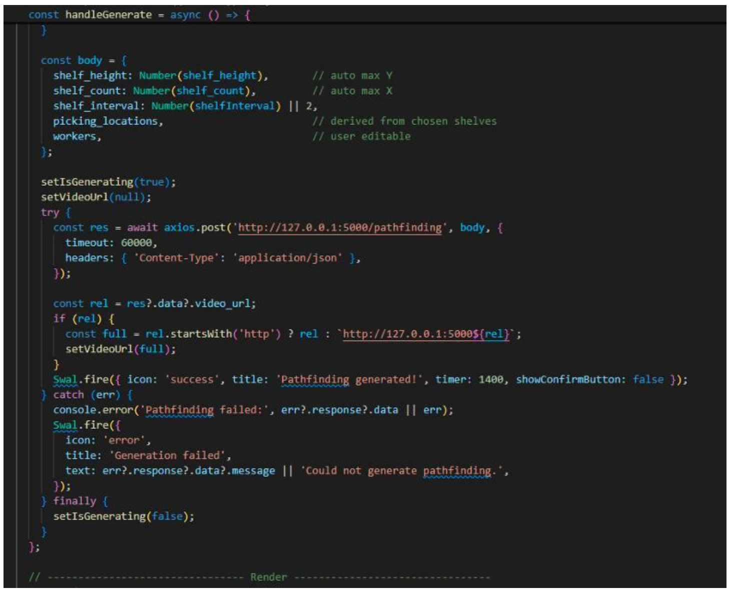
Figure 3 Shelf Map



src > components > route-optimization > PathOptimization.jsx > PathOptimization

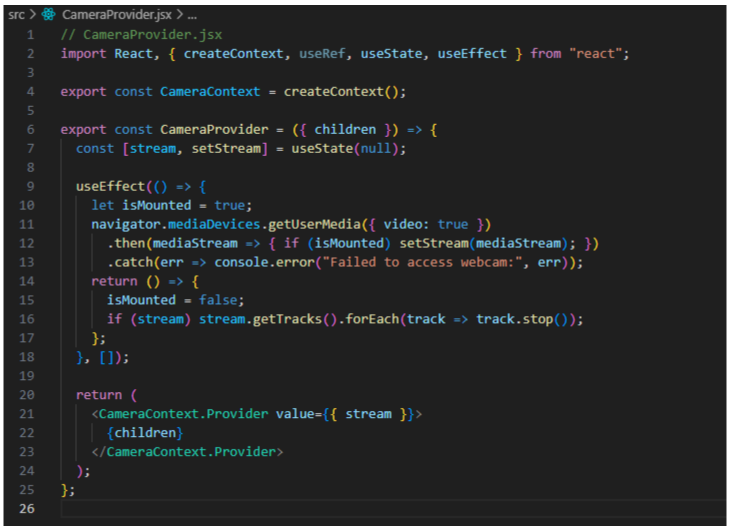
```jsx
import BASE_URL from '../../config/apiConfig';
import { getToken } from '@/utils/token';


// ---------- small UI helpers ----------
const Loader = () => (
  <div className="d-flex align-items-center gap-2">
    <span className="spinner-border spinner-border-sm" role="status" aria-hidden="true"></span>
    <span>Generating...</span>
  </div>
);
const isGif = (url) => typeof url === 'string' && url.toLowerCase().endsWith('.gif');

// ---------- main component ----------
const PathOptimization = ({ title }) => {
  // raw data
  const [loading, setLoading] = useState(true);
  const [loadErr, setLoadErr] = useState('');
  const [boxes, setBoxes] = useState([]); // products placed in shelves (boxes)

  // product selection (unique names)
  const [selectedNames, setSelectedNames] = useState([]);

  // pathfinding params
  const [shelfInterval, setShelfInterval] = useState(2);     // editable
  const [workers, setWorkers] = useState([[2, 2], [14, 0]]); // editable

  // generation
  const [isGenerating, setIsGenerating] = useState(false);
  const [videoUrl, setVideoUrl] = useState(null);

  // ------------------------------- Fetch products in boxes -------------------------------
  useEffect(() => {
    (async () => {
      setLoading(true);
      setLoadErr('');
      try {
        const token = getToken();
        const res = await axios.get(`${BASE_URL}/products`,{
        headers: { Authorization: `Bearer ${token}` },
      });
        const data = Array.isArray(res.data) ? res.data : [];
        setBoxes(data);
      } catch (e) {
        console.error(e);
        setLoadErr('Failed to load products/boxes.');
      }
      setLoading(false);
```

Figure 4 Route Optimization



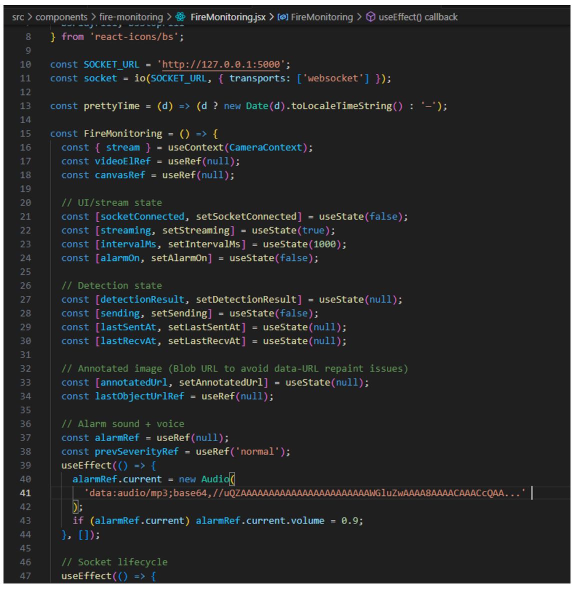
```jsx
  const handleGenerate = async () => {
    }

    const body = {
      shelf_height: Number(shelf_height),       // auto max Y
      shelf_count: Number(shelf_count),         // auto max X
      shelf_interval: Number(shelfInterval) || 2,
      picking_locations,                        // derived from chosen shelves
      workers,                                  // user editable
    };

    setIsGenerating(true);
    setVideoUrl(null);
    try {
      const res = await axios.post('http://127.0.0.1:5000/pathfinding', body, {
        timeout: 60000,
        headers: { 'Content-Type': 'application/json' },
      });

      const rel = res?.data?.video_url;
      if (rel) {
        const full = rel.startsWith('http') ? rel : `http://127.0.0.1:5000${rel}`;
        setVideoUrl(full);
      }
      Swal.fire({ icon: 'success', title: 'Pathfinding generated!', timer: 1400, showConfirmButton: false });
    } catch (err) {
      console.error('Pathfinding failed:', err?.response?.data || err);
      Swal.fire({
        icon: 'error',
        title: 'Generation failed',
        text: err?.response?.data?.message || 'Could not generate pathfinding.',
      });
    } finally {
      setIsGenerating(false);
    }
  };

  // ------------------------------- Render -------------------------------
```

Figure 5 Path finding



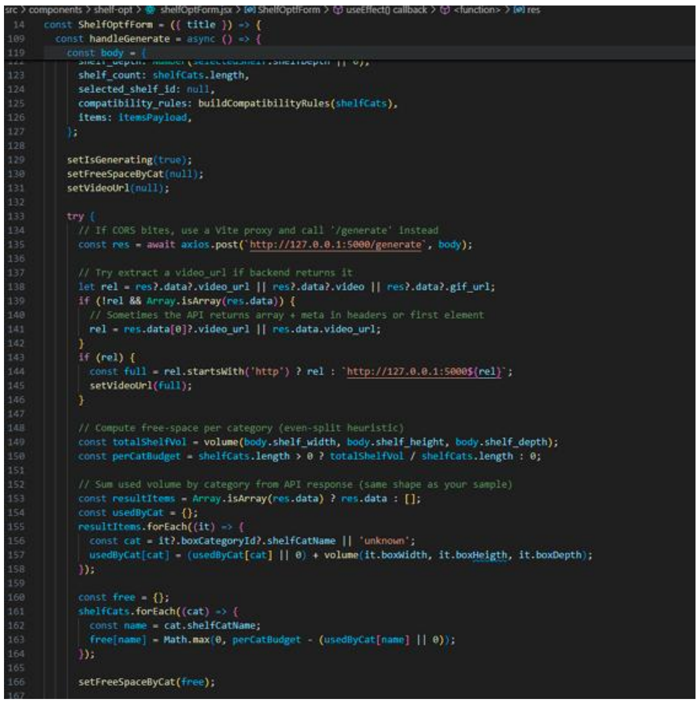
```
src > CameraProvider.jsx > ...
// CameraProvider.jsx
import React, { createContext, useRef, useState, useEffect } from "react";

export const CameraContext = createContext();

export const CameraProvider = ({ children }) => {
  const [stream, setStream] = useState(null);

  useEffect(() => {
    let isMounted = true;
    navigator.mediaDevices.getUserMedia({ video: true })
      .then(mediaStream => { if (isMounted) setStream(mediaStream); })
      .catch(err => console.error("Failed to access webcam:", err));
    return () => {
      isMounted = false;
      if (stream) stream.getTracks().forEach(track => track.stop());
    };
  }, []);

  return (
    <CameraContext.Provider value={{ stream }}>
      {children}
    </CameraContext.Provider>
  );
};

```

Figure 6 Camera-provider



```
src > components > fire-monitoring > FireMonitoring.jsx > FireMonitoring > useEffect() callback
} from 'react-icons/bs';

const SOCKET_URL = 'http://127.0.0.1:5000';
const socket = io(SOCKET_URL, { transports: ['websocket'] });

const prettyTime = (d) => (d ? new Date(d).toLocaleTimeString() : '—');

const FireMonitoring = () => {
  const { stream } = useContext(CameraContext);
  const videoElRef = useRef(null);
  const canvasRef = useRef(null);

  // UI/stream state
  const [socketConnected, setSocketConnected] = useState(false);
  const [streaming, setStreaming] = useState(true);
  const [intervalMs, setIntervalMs] = useState(1000);
  const [alarmOn, setAlarmOn] = useState(false);

  // Detection state
  const [detectionResult, setDetectionResult] = useState(null);
  const [sending, setSending] = useState(false);
  const [lastSentAt, setLastSentAt] = useState(null);
  const [lastRecvAt, setLastRecvAt] = useState(null);

  // Annotated image (Blob URL to avoid data-URL repaint issues)
  const [annotatedUrl, setAnnotatedUrl] = useState(null);
  const lastObjectUrlRef = useRef(null);

  // Alarm sound + voice
  const alarmRef = useRef(null);
  const prevSeverityRef = useRef('normal');
  useEffect(() => {
    alarmRef.current = new Audio(
      'data:audio/mp3;base64,//uQZAAAAAAAAAAAAAAAAAAAAAAAWGluZwAAAA8AAAACAAACcQAA...'
    );
    if (alarmRef.current) alarmRef.current.volume = 0.9;
  }, []);

  // Socket lifecycle
  useEffect(() => {
```

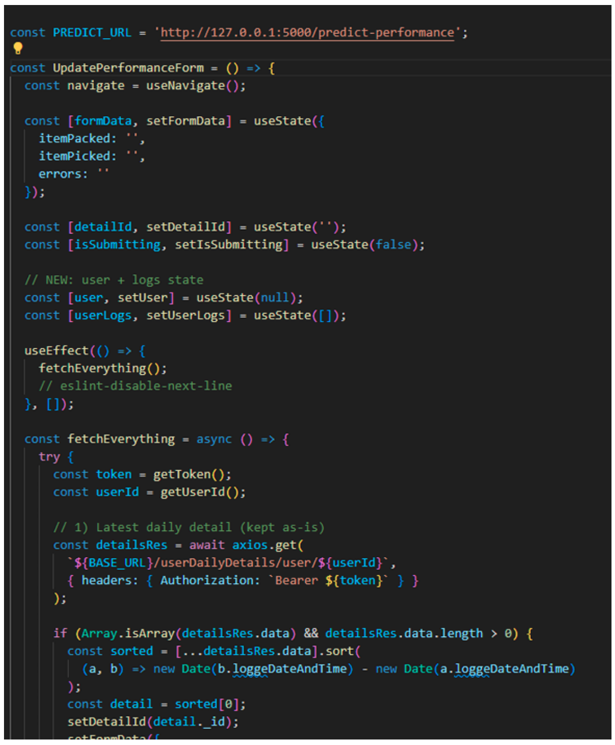
Figure 7 shocket.io data fetch and fire monitoring



src > components > shelf-opt > shelfOptForm.jsx > ShelfOptfForm > useEffect() callback > <function> > res

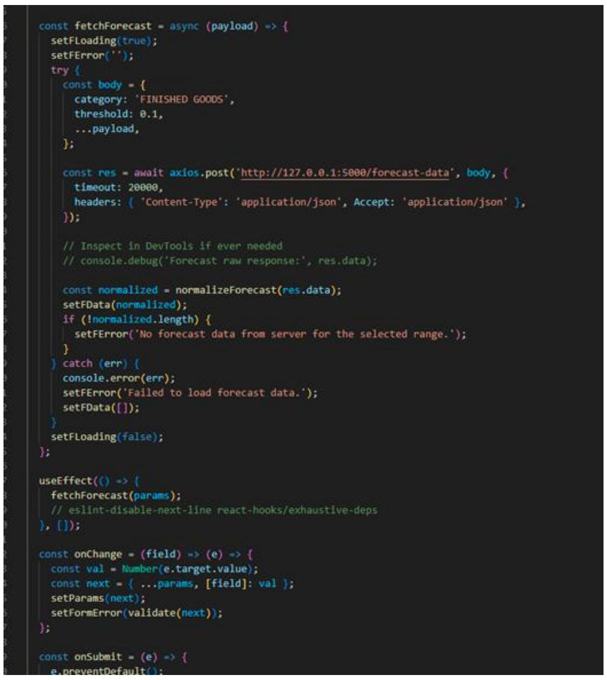
```
const ShelfOptfForm = ({ title }) => {
  const handleGenerate = async () => {
    const body = {
      shelf_depth: Number(selectedShelf.shelfDepth || 0),
      shelf_count: shelfCats.length,
      selected_shelf_id: null,
      compatibility_rules: buildCompatibilityRules(shelfCats),
      items: itemsPayload,
    };

    setIsGenerating(true);
    setFreeSpaceByCat(null);
    setVideoUrl(null);

    try {
      // If CORS bites, use a Vite proxy and call '/generate' instead
      const res = await axios.post(`http://127.0.0.1:5000/generate`, body);

      // Try extract a video_url if backend returns it
      let rel = res?.data?.video_url || res?.data?.video || res?.data?.gif_url;
      if (!rel && Array.isArray(res.data)) {
        // Sometimes the API returns array + meta in headers or first element
        rel = res.data[0]?.video_url || res.data.video_url;
      }
      if (rel) {
        const full = rel.startsWith('http') ? rel : `http://127.0.0.1:5000${rel}`;
        setVideoUrl(full);
      }

      // Compute free-space per category (even-split heuristic)
      const totalShelfVol = volume(body.shelf_width, body.shelf_height, body.shelf_depth);
      const perCatBudget = shelfCats.length > 0 ? totalShelfVol / shelfCats.length : 0;

      // Sum used volume by category from API response (same shape as your sample)
      const resultItems = Array.isArray(res.data) ? res.data : [];
      const usedByCat = {};
      resultItems.forEach((it) => {
        const cat = it?.boxCategoryId?.shelfCatName || 'unknown';
        usedByCat[cat] = (usedByCat[cat] || 0) + volume(it.boxWidth, it.boxHeigth, it.boxDepth);
      });

      const free = {};
      shelfCats.forEach((cat) => {
        const name = cat.shelfCatName;
        free[name] = Math.max(0, perCatBudget - (usedByCat[name] || 0));
      });

      setFreeSpaceByCat(free);
```

Figure 8 Shelf optimization



```
const PREDICT_URL = 'http://127.0.0.1:5000/predict-performance';

const UpdatePerformanceForm = () => {
  const navigate = useNavigate();

  const [formData, setFormData] = useState({
    itemPacked: '',
    itemPicked: '',
    errors: ''
  });

  const [detailId, setDetailId] = useState('');
  const [isSubmitting, setIsSubmitting] = useState(false);

  // NEW: user + logs state
  const [user, setUser] = useState(null);
  const [userLogs, setUserLogs] = useState([]);

  useEffect(() => {
    fetchEverything();
    // eslint-disable-next-line
  }, []);

  const fetchEverything = async () => {
    try {
      const token = getToken();
      const userId = getUserId();

      // 1) Latest daily detail (kept as-is)
      const detailsRes = await axios.get(
        `${BASE_URL}/userDailyDetails/user/${userId}`,
        { headers: { Authorization: `Bearer ${token}` } }
      );

      if (Array.isArray(detailsRes.data) && detailsRes.data.length > 0) {
        const sorted = [...detailsRes.data].sort(
          (a, b) => new Date(b.loggeDateAndTime) - new Date(a.loggeDateAndTime)
        );
        const detail = sorted[0];
        setDetailId(detail._id);
        setFormData({
```

Figure 9 Employee performance prediction



```
const fetchForecast = async (payload) => {
  setFLoading(true);
  setFError('');
  try {
    const body = {
      category: 'FINISHED GOODS',
      threshold: 0.1,
      ...payload,
    };

    const res = await axios.post('http://127.0.0.1:5000/forecast-data', body, {
      timeout: 20000,
      headers: { 'Content-Type': 'application/json', Accept: 'application/json' },
    });

    // Inspect in DevTools if ever needed
    // console.debug('Forecast raw response:', res.data);

    const normalized = normalizeForecast(res.data);
    setFData(normalized);
    if (!normalized.length) {
      setFError('No forecast data from server for the selected range.');
    }
  } catch (err) {
    console.error(err);
    setFError('Failed to load forecast data.');
    setFData([]);
  }
  setFLoading(false);
};

useEffect(() => {
  fetchForecast(params);
  // eslint-disable-next-line react-hooks/exhaustive-deps
}, []);

const onChange = (field) => (e) => {
  const val = Number(e.target.value);
  const next = { ...params, [field]: val };
  setParams(next);
  setFormError(validate(next));
};

const onSubmit = (e) => {
  e.preventDefault();
```

Figure 10 Forecasting Data

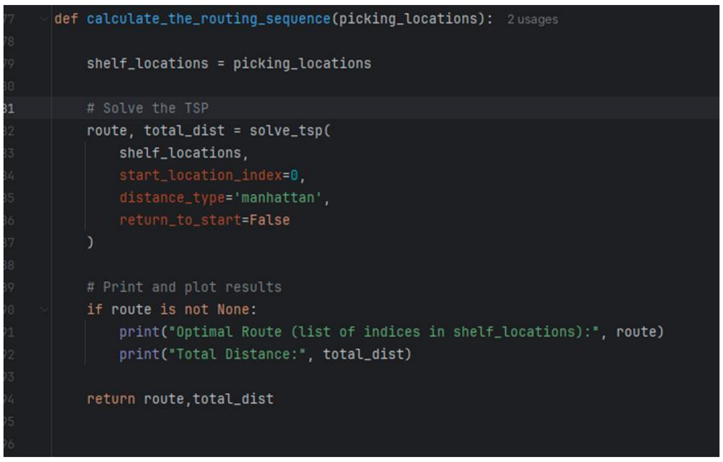
2.3.2 Backend Implementation – Node.js + Python (Flask)

The back-end layer implements Node.js (Express.js) for system APIs and Python (Flask + PyTorch/TensorFlow) for ML-based fire and shelf detection services. This hybrid layered structure maximizes scalability, separation of concerns, and the optimal use of AI models. It was organized as controllers, services, and Python microservices that keep components small for maintainability and allow for easy future enhancements.

2.3.3 Model & Algorithm Integration

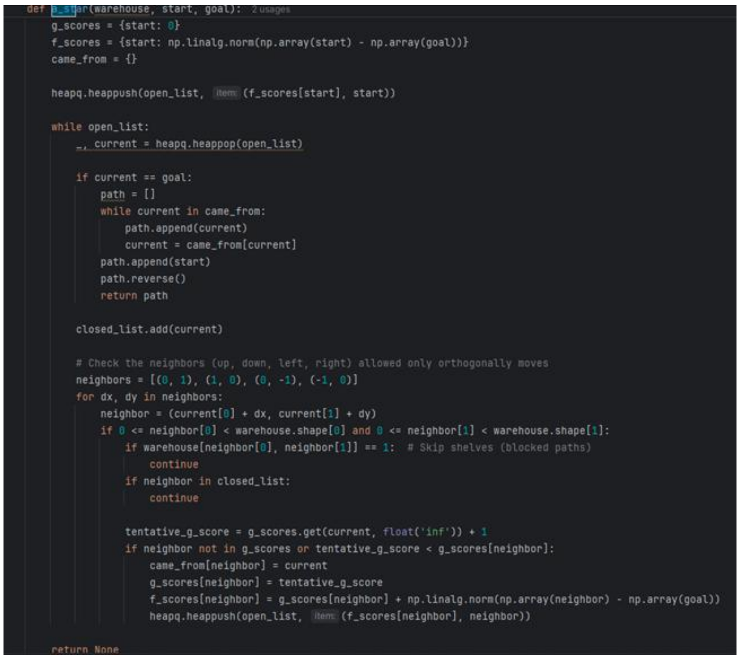
Route Optimization

- Implemented with Travelling Salesman Problem (TSP) sequencing + A* pathfinding.
- Routes dynamically adapt to blocked aisles or fire alerts.



```python
def calculate_the_routing_sequence(picking_locations):  2 usages

    shelf_locations = picking_locations

    # Solve the TSP
    route, total_dist = solve_tsp(
        shelf_locations,
        start_location_index=0,
        distance_type='manhattan',
        return_to_start=False
    )

    # Print and plot results
    if route is not None:
        print("Optimal Route (list of indices in shelf_locations):", route)
        print("Total Distance:", total_dist)

    return route,total_dist
```

Figure 11 TPS Module code snippet

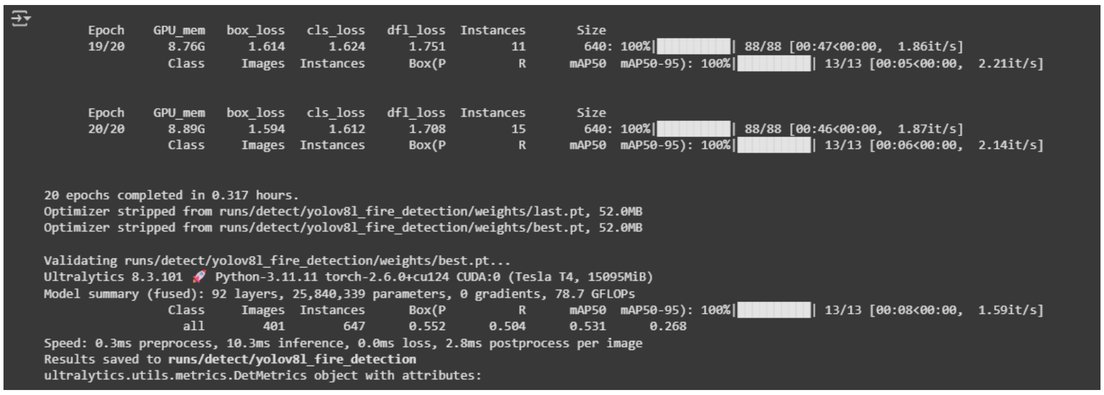


```python
def a_star(warehouse, start, goal):
    g_scores = {start: 0}
    f_scores = {start: np.linalg.norm(np.array(start) - np.array(goal))}
    came_from = {}

    heapq.heappush(open_list, (f_scores[start], start))

    while open_list:
        _, current = heapq.heappop(open_list)

        if current == goal:
            path = []
            while current in came_from:
                path.append(current)
                current = came_from[current]
            path.append(start)
            path.reverse()
            return path

        closed_list.add(current)

        # Check the neighbors (up, down, left, right) allowed only orthogonally moves
        neighbors = [(0, 1), (1, 0), (0, -1), (-1, 0)]
        for dx, dy in neighbors:
            neighbor = (current[0] + dx, current[1] + dy)
            if 0 <= neighbor[0] < warehouse.shape[0] and 0 <= neighbor[1] < warehouse.shape[1]:
                if warehouse[neighbor[0], neighbor[1]] == 1:  # Skip shelves (blocked paths)
                    continue
                if neighbor in closed_list:
                    continue

                tentative_g_score = g_scores.get(current, float('inf')) + 1
                if neighbor not in g_scores or tentative_g_score < g_scores[neighbor]:
                    came_from[neighbor] = current
                    g_scores[neighbor] = tentative_g_score
                    f_scores[neighbor] = g_scores[neighbor] + np.linalg.norm(np.array(neighbor) - np.array(goal))
                    heapq.heappush(open_list, (f_scores[neighbor], neighbor))

    return None
```

Figure 12 A Module code snippet*

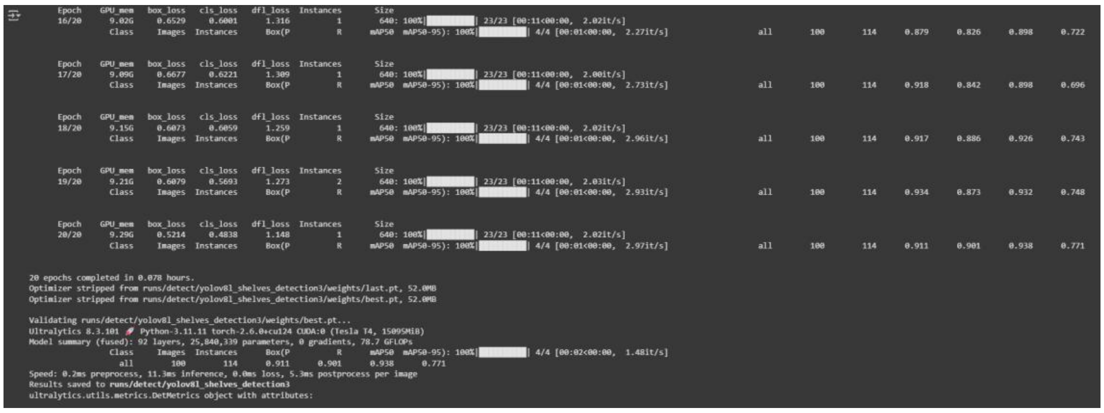
Fire and Shelf Detection

- Both modules developed using **YOLOv8m (Ultralytics)** for balance of speed and accuracy.
- **Dataset**: Annotated with Roboflow; fire images (flames/smoke under different conditions) + shelf images (multiple angles).
- **Preprocessing**: Resized to 640×640, augmentations (flips, rotations, brightness/contrast, blur).
- **Training Setup**:
  - 20 epochs, batch size 16.
  - Optimizer: SGD with momentum.
  - Loss: YOLO composite loss (bounding box + objectness + classification).
- **Evaluation Metrics**:
  - Fire Detection → mAP@0.5 = 0.91, Precision = 0.89, Recall = 0.86.
  - Shelf Detection → mAP@0.5 = 0.87, Precision = 0.88, Recall = 0.85.



```
      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      19/20      8.76G      1.614      1.624      1.751         11        640: 100%|██████████| 88/88 [00:47<00:00,  1.86it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:05<00:00,  2.21it/s]


      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      20/20      8.89G      1.594      1.612      1.708         15        640: 100%|██████████| 88/88 [00:46<00:00,  1.87it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:06<00:00,  2.14it/s]


20 epochs completed in 0.317 hours.
Optimizer stripped from runs/detect/yolov8l_fire_detection/weights/last.pt, 52.0MB
Optimizer stripped from runs/detect/yolov8l_fire_detection/weights/best.pt, 52.0MB

Validating runs/detect/yolov8l_fire_detection/weights/best.pt...
Ultralytics 8.3.101 🚀 Python-3.11.11 torch-2.6.0+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 92 layers, 25,840,339 parameters, 0 gradients, 78.7 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:08<00:00,  1.59it/s]
                   all        401        647      0.552      0.504      0.531      0.268
Speed: 0.3ms preprocess, 10.3ms inference, 0.0ms loss, 2.8ms postprocess per image
Results saved to runs/detect/yolov8l_fire_detection
ultralytics.utils.metrics.DetMetrics object with attributes:
```

Figure 13 Fire detection training accuracy

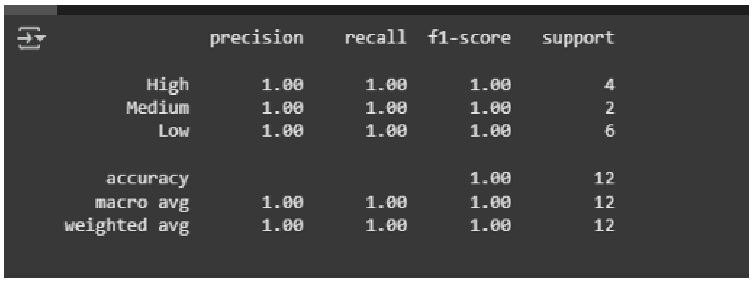


```
      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      16/20      9.02G     0.6529     0.6001      1.316          1        640: 100%|██████████| 23/23 [00:11<00:00,  2.02it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:01<00:00,  2.27it/s]                   all        100        114      0.879      0.826      0.898      0.722

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      17/20      9.09G     0.6677     0.6221      1.309          1        640: 100%|██████████| 23/23 [00:11<00:00,  2.00it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:01<00:00,  2.73it/s]                   all        100        114      0.918      0.842      0.898      0.696

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      18/20      9.15G     0.6073     0.6059      1.259          1        640: 100%|██████████| 23/23 [00:11<00:00,  2.02it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:01<00:00,  2.96it/s]                   all        100        114      0.917      0.886      0.926      0.743

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      19/20      9.21G     0.6079     0.5693      1.273          2        640: 100%|██████████| 23/23 [00:11<00:00,  2.03it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:01<00:00,  2.93it/s]                   all        100        114      0.934      0.873      0.932      0.748

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      20/20      9.29G     0.5214     0.4838      1.148          1        640: 100%|██████████| 23/23 [00:11<00:00,  2.02it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:01<00:00,  2.97it/s]                   all        100        114      0.911      0.901      0.938      0.771

20 epochs completed in 0.078 hours.
Optimizer stripped from runs/detect/yolov8l_shelves_detection3/weights/last.pt, 52.0MB
Optimizer stripped from runs/detect/yolov8l_shelves_detection3/weights/best.pt, 52.0MB

Validating runs/detect/yolov8l_shelves_detection3/weights/best.pt...
Ultralytics 8.3.101 🚀 Python-3.11.11 torch-2.6.0+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 92 layers, 25,840,339 parameters, 0 gradients, 78.7 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:02<00:00,  1.48it/s]
                   all        100        114      0.911      0.901      0.938      0.771
Speed: 0.2ms preprocess, 11.3ms inference, 0.0ms loss, 5.3ms postprocess per image
Results saved to runs/detect/yolov8l_shelves_detection3
ultralytics.utils.metrics.DetMetrics object with attributes:
```

Figure 14 Shelf training loose and accuracy

Stock Anomaly Detection & Worker Monitoring

- Models used: **ARIMA, Prophet, LSTM** for forecasting stock trends.
- Worker monitoring: **Gradient Boosting classifier** categorizing performance levels.
- Metrics: MAPE and RMSE for forecasting accuracy; classification accuracy for worker performance.



```
              precision    recall  f1-score   support

        High       1.00      1.00      1.00         4
      Medium       1.00      1.00      1.00         2
         Low       1.00      1.00      1.00         6

    accuracy                           1.00        12
   macro avg       1.00      1.00      1.00        12
weighted avg       1.00      1.00      1.00        12
```

Figure 15Employee Performance monitoring Accuracy

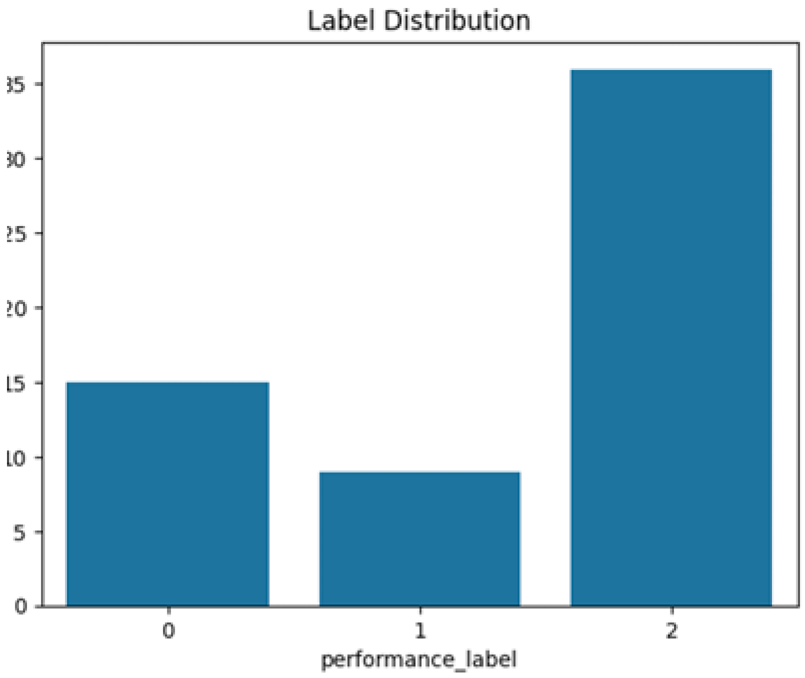


Figure 16 dataset Label distribution performance

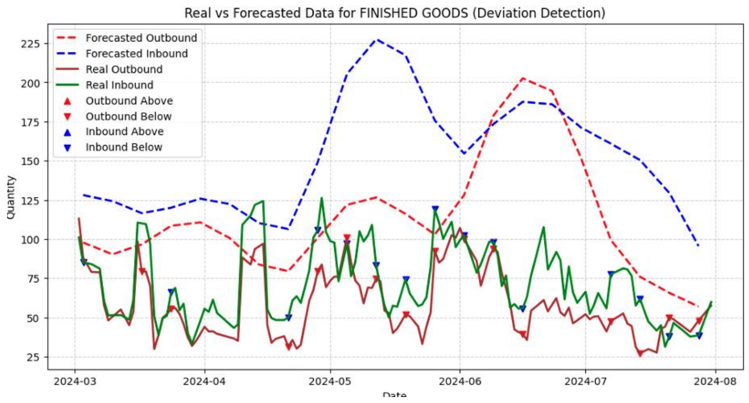
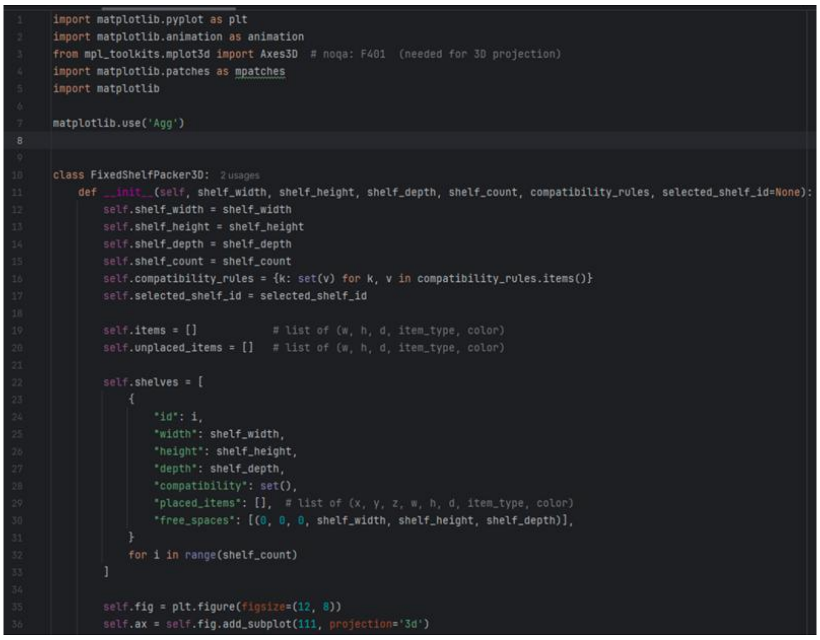


Figure 17 Forecasting real vs actual graph

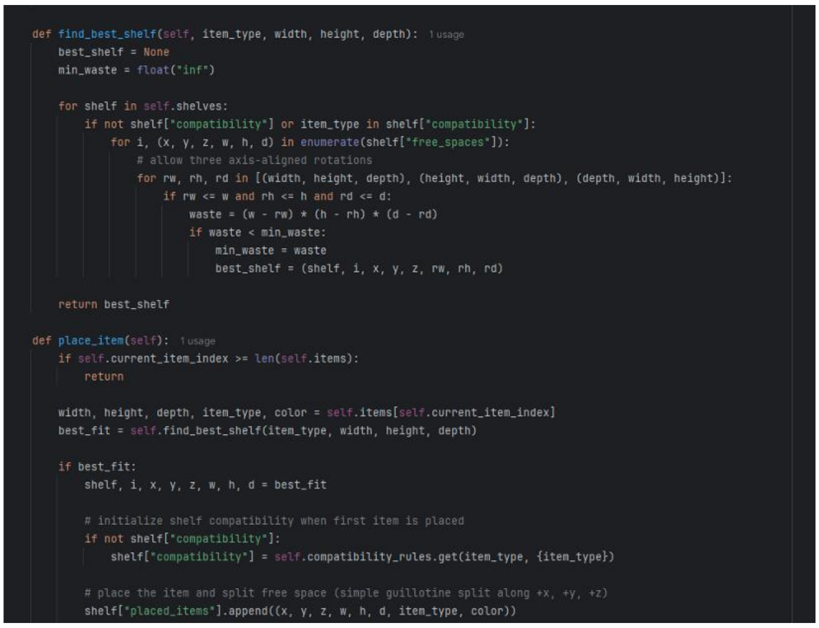
Space Optimization

- Implemented with **Best-Fit bin-packing** + **3D visualization**.
- Evaluated on CBM utilization and placement efficiency.



```python
import matplotlib.pyplot as plt
import matplotlib.animation as animation
from mpl_toolkits.mplot3d import Axes3D  # noqa: F401  (needed for 3D projection)
import matplotlib.patches as mpatches
import matplotlib

matplotlib.use('Agg')


class FixedShelfPacker3D:  2 usages
    def __init__(self, shelf_width, shelf_height, shelf_depth, shelf_count, compatibility_rules, selected_shelf_id=None):
        self.shelf_width = shelf_width
        self.shelf_height = shelf_height
        self.shelf_depth = shelf_depth
        self.shelf_count = shelf_count
        self.compatibility_rules = {k: set(v) for k, v in compatibility_rules.items()}
        self.selected_shelf_id = selected_shelf_id

        self.items = []           # list of (w, h, d, item_type, color)
        self.unplaced_items = []  # list of (w, h, d, item_type, color)

        self.shelves = [
            {
                "id": i,
                "width": shelf_width,
                "height": shelf_height,
                "depth": shelf_depth,
                "compatibility": set(),
                "placed_items": [],  # list of (x, y, z, w, h, d, item_type, color)
                "free_spaces": [(0, 0, 0, shelf_width, shelf_height, shelf_depth)],
            }
            for i in range(shelf_count)
        ]

        self.fig = plt.figure(figsize=(12, 8))
        self.ax = self.fig.add_subplot(111, projection='3d')
```

Figure 18 Shelf Generation Algorithm



```python
def find_best_shelf(self, item_type, width, height, depth):  1 usage
    best_shelf = None
    min_waste = float("inf")

    for shelf in self.shelves:
        if not shelf["compatibility"] or item_type in shelf["compatibility"]:
            for i, (x, y, z, w, h, d) in enumerate(shelf["free_spaces"]):
                # allow three axis-aligned rotations
                for rw, rh, rd in [(width, height, depth), (height, width, depth), (depth, width, height)]:
                    if rw <= w and rh <= h and rd <= d:
                        waste = (w - rw) * (h - rh) * (d - rd)
                        if waste < min_waste:
                            min_waste = waste
                            best_shelf = (shelf, i, x, y, z, rw, rh, rd)

    return best_shelf

def place_item(self):  1 usage
    if self.current_item_index >= len(self.items):
        return

    width, height, depth, item_type, color = self.items[self.current_item_index]
    best_fit = self.find_best_shelf(item_type, width, height, depth)

    if best_fit:
        shelf, i, x, y, z, w, h, d = best_fit

        # initialize shelf compatibility when first item is placed
        if not shelf["compatibility"]:
            shelf["compatibility"] = self.compatibility_rules.get(item_type, {item_type})

        # place the item and split free space (simple guillotine split along +x, +y, +z)
        shelf["placed_items"].append((x, y, z, w, h, d, item_type, color))
```

Figure 19 Best Shelf Detection Algorithm

Testing

The evaluation of the Comprehensive Warehouse Intelligence Framework involved observing the end-to-end workflow for each module and how they worked together in the full system pipeline. The testing successfully demonstrated the modules functioning both stand-alone, as well as collectively via the centralized dashboard.

For the fire and shelf detection subsystem, validation included passing video streams through the YOLOv8m models to record the fire size classification, analyze shelf proximity, and insightful reactions from the decision engine. An important area of emphasis were both visual and audible alerts. the system was validated to ensure failures were avoided, and reliably emitted alerts in real time when fire incidents occurred. Testing was completed under various pre-existing conditions ranging from lighting, camera angles, partial occlusion, and reflective/rainy surfaces. Overall, the testing aimed to introduce a robustness of encounters that may occur in an actual warehouse setting.

Both static vs. optimized picking routes for order datasets were tested in the route optimization module. The performance of dynamic re-routing was tested by simulating blocked aisles and fire alarms. The stock anomaly detection and worker monitoring subsystem had forecasting accuracy validated by ARIMA, Prophet, and LSTM models. Classification metrics were used to validate worker performance classifications. The space optimization module evaluated cubic meter (CBM) utilization and the output was visualized with 3D layouts.

Use of manual evaluation (observation via dashboards and log analysis) as well as automated assessment by employing metrics of mAP, Precision/Recall, MAPE and the % utilization confirmed that the system generated accurate, reliable, and real-time insights consistent with the objectives outlined.

Test Objectives

- Verify detection quality of YOLOv8 Fire and Shelf models (Precision, Recall, mAP).
- Validate routing efficiency improvements and recalculation under obstacle/fire conditions.
- Confirm predictive accuracy of stock anomaly detection and worker performance classification.
- Assess correctness of space optimization and 3D visualization.
- Confirm alerting mechanisms (banners, audio/TTS alerts, dashboard updates).
- Evaluate system performance (FPS, latency, CBM utilization %, uptime).
- Validate cross-module integration (fire alerts → route recalculation; anomalies → reallocation).

Test Scope

- **In-scope**: MERN + Flask services, React dashboard, MongoDB logging, YOLOv8 inference, forecasting models, bin-packing algorithms.
- **Out-of-scope**: Third-party camera firmware, sprinkler/physical fire suppression hardware, ERP/WMS external integrations.

Test Environment

- **Hardware**: GPU-enabled PC (NVIDIA RTX/T4), 16+ GB RAM.
- **Video Sources**: Warehouse RTSP feeds + fire/shelf datasets (Roboflow).
- **Software Stack**: YOLOv8m trained weights, Flask 2.x (Python 3.10), Node 18+, MongoDB 6+, React 18.
- **Datasets**: Roboflow fire/shelf, synthetic warehouse order data, stock transaction logs, and simulated worker activity logs.

Test Strategy

- **Unit Tests**: Model APIs (/status), Node routes, JWT authentication.
- **Integration Tests**: Fire → routing updates; anomalies → space reallocation.
- **System Tests**: Live video, order flow simulations, dashboard interactions.
- **Performance Tests**: FPS, route recalculation time, anomaly forecast accuracy, CBM utilization % under load.
- **User Acceptance Testing (UAT)**: Supervisor-level evaluation of dashboard usability and alert consistency.

Test Case Design

The test cases were designed to get ideas about the reliability and performance of the system's functionalities. Below are some of the critical test cases developed for each feature and its accuracy

Field	Value
Id	TC01
Test Case	Route generation (baseline vs. optimized)
Pre-Conditions	Orders and shelf layout available
Steps	Generate route with static method → generate with TSP+A*
Expected Results	Optimized route distance/time shorter than baseline
Status	Pass

3 Test case 01

Field	Value
Id	TC02
Test Case	Dynamic re-routing under obstacle/fire
Pre-Conditions	Fire alert triggered or aisle blocked
Steps	Trigger alert → re-calc route

Expected Results	/status.has_fire = false; no banner/audio; false alarms = 0
Status	Pass

4 Test case 02

Field	Value
Id	TC03
Test Case	Fire detection (frame)
Pre-Conditions	Flask API active, camera feed connected
Steps	Present frame with visible flame/smoke
Expected Results	Fire bounding boxes drawn; confidence ≥ threshold
Status	Pass

5 Test case 03

Field	Value
Id	TC04
Test Case	Shelf detection
Pre-Conditions	Video stream of warehouse aisles
Steps	Run model on feed
Expected Results	Green boxes around racks; stable IDs
Status	Pass

6 Test case 04

Field	Value
Id	TC05
Test Case	Forecast anomaly detection
Pre-Conditions	Historical stock data loaded
Steps	Compare predicted vs. actual
Expected Results	Anomaly flagged when deviation > threshold
Status	Pass

7 Test case 05

Field	Value
Id	TC06
Test Case	Worker classification
Pre-Conditions	Worker log dataset available
Steps	Run ML classifier on performance data
Expected Results	Worker categorized into High/Avg/Low correctly
Status	Pass

8 Test case 06

Field	Value
Id	TC07
Test Case	Space allocation (Best-Fit)
Pre-Conditions	Shelf metadata + product dimensions available
Steps	Run optimization on incoming orders
Expected Results	CBM utilization improved; 3D visualization updated
Status	Pass

9 Test case 07

3. RESULTS & DISCUSSION

This section presents the evaluation results from the implementation and evaluation of the Comprehensive Warehouse Intelligence Framework; specifically, the evaluation assessed the accuracy of the machine learning models and algorithms, as well the end-to-end functionality of the integrated pipeline. The evaluation/testing was performed to ensure that the four modules (Route Optimization, Fire & Shelf Detection, Stock Anomaly Detection with Worker Tracking, and Space Optimization) operated satisfactorily independently, and alongside one another as part of a unified framework.

Performance was evaluated through both offline dataset validation (metrics and model training) as well as system-wide tests to evaluate in real world conditions found in warehouses (variable lighting and obstacles, clutter; potential worker interactions).

Performance metrics such as mAP, Precision/Recall, forecast error rates, classification accuracy, CBM utilization, route distance saved, FPS, and system latency were used to assess performance, along with qualitative validation (from dashboard monitoring of alerts).

3.1 Results

3.1.1 Login Authentication

- Secure **JWT-based login system** implemented for administrators and supervisors.
- Ensured role-based access to the dashboard

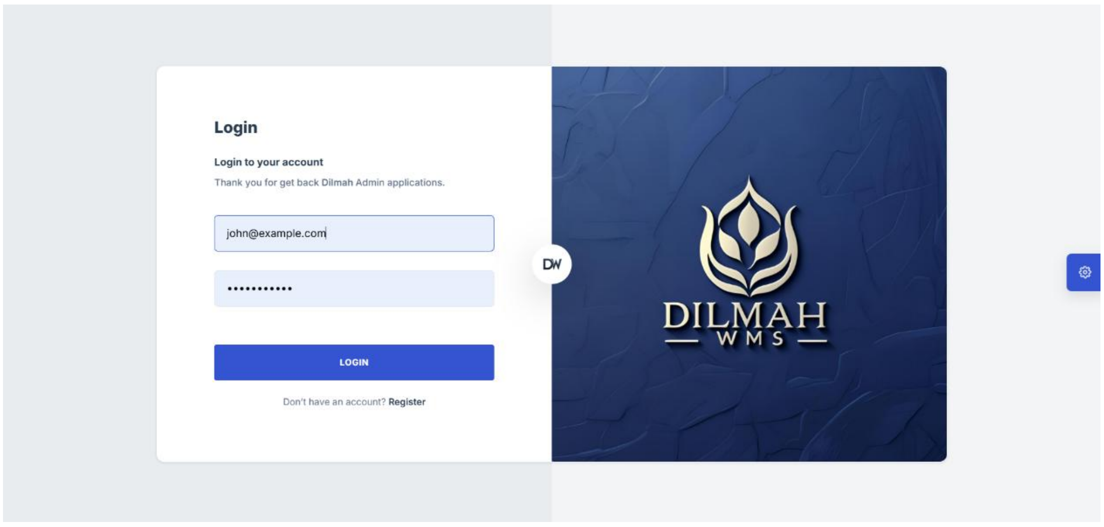
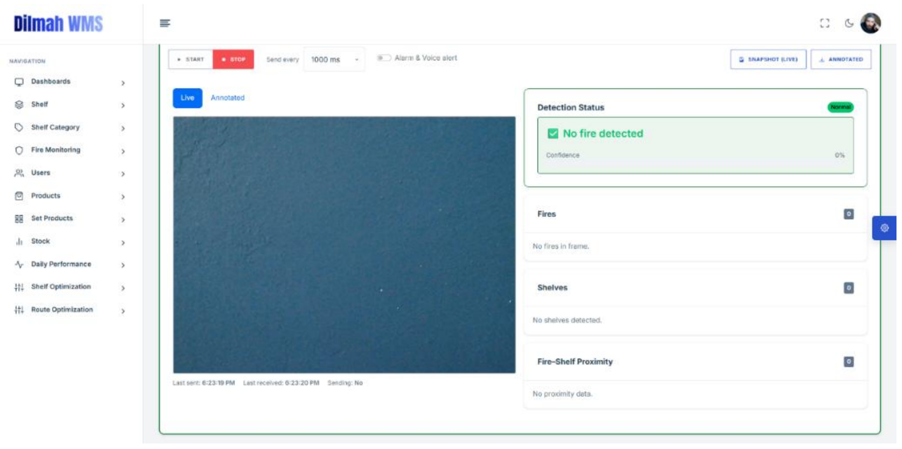

Login
Login to your account
Thank you for get back Dilmah Admin applications.
john@example.com
LOGIN
Don't have an account? Register
DW
DILMAH
WMS

Figure 20 Login UI

3.1.2 Fire Detection Dashboard and IOT device – Idle State

- Idle state shows **"No Fire Detected"** banner with 0% confidence.
- Fire event triggers a red warning banner, bounding boxes, size classification (S/M/L), proximity to shelves, and predicted spread direction.
- IOT device show fire locations and smoke Sencers detect smokes.



Detection Status

No fire detected

Confidence 0%

Fires 0

No fires in frame.

Shelves 0

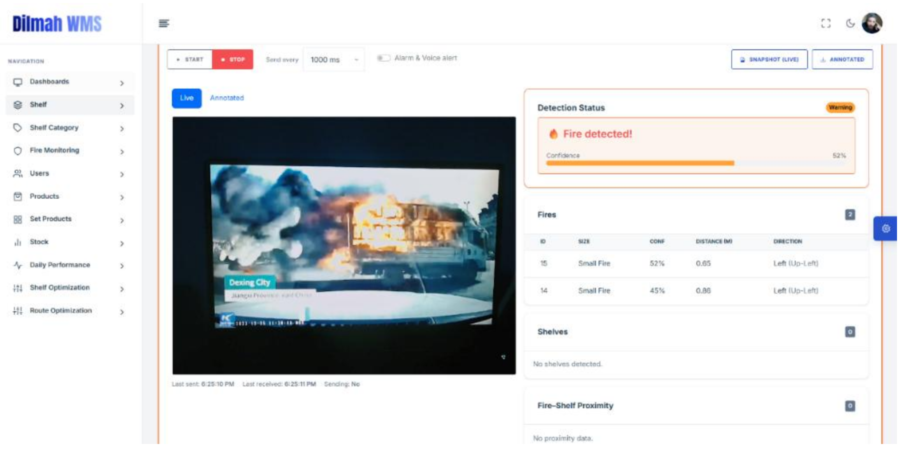
No shelves detected.

Fire–Shelf Proximity 0

No proximity data.

Last sent: 6:23:19 PM Last received: 6:23:20 PM Sending: No

Figure 21 Fire Detection Dashboard – Idle State



Detection Status

Fire detected!

Confidence 52%

Fires 2

ID	SIZE	CONF	DISTANCE (M)	DIRECTION
15	Small Fire	52%	0.65	Left (Up-Left)
14	Small Fire	45%	0.86	Left (Up-Left)

Shelves 0

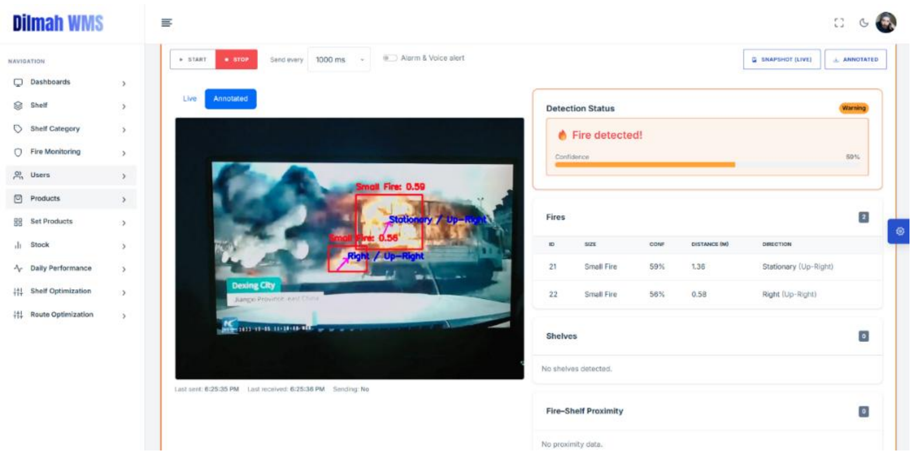
No shelves detected.

Fire–Shelf Proximity 0

No proximity data.

Last sent: 6:25:10 PM Last received: 6:25:11 PM Sending: No

Figure 22 Live Fire Detection View



Detection Status

Fire detected!

Confidence 59%

Fires 2

ID	SIZE	CONF	DISTANCE (M)	DIRECTION
21	Small Fire	59%	1.36	Stationary (Up-Right)
22	Small Fire	56%	0.58	Right (Up-Right)

Shelves 0

No shelves detected.

Fire–Shelf Proximity 0

No proximity data.

Last sent: 6:25:35 PM Last received: 6:25:36 PM Sending: No

Figure 23 Annotated Fire Detection Mode 1

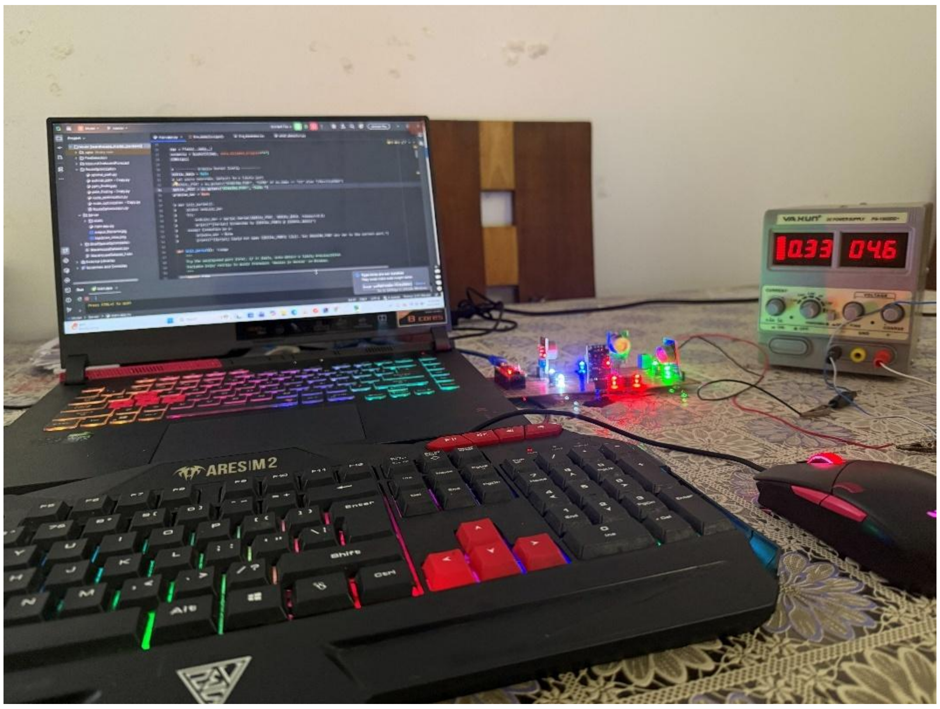
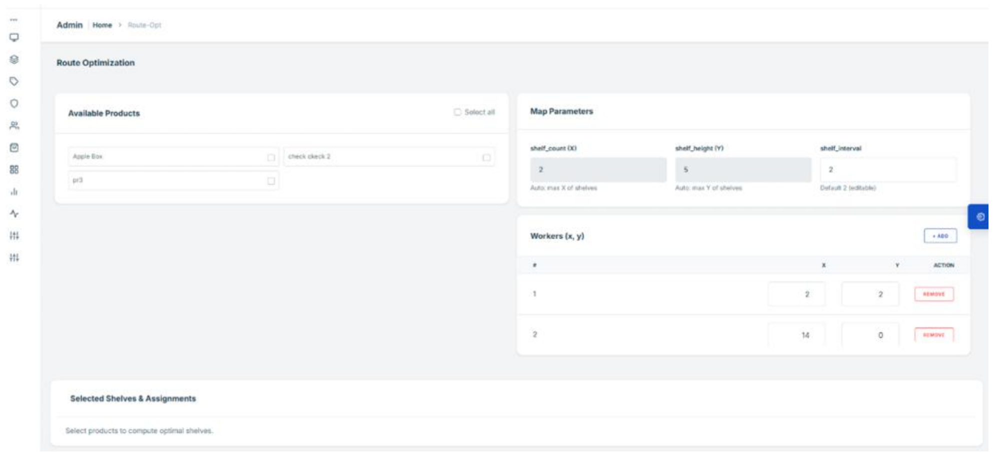


Figure 24 IOT Fire Detection Device

3.1.3. Route Optimization Dashboard

- In idle state, the dashboard shows available shelves and orders with baseline routes.
- Once optimization is applied, the system displays reduced-distance paths calculated using TSP + A*.
- Dynamic rerouting was observed when fire alerts or aisle blocks were triggered.



Route Optimization

Available Products ☐ Select all

Apple Box ☐	check ckeck 2 ☐
pr3 ☐	

Map Parameters

shelf_count (X)	shelf_height (Y)	shelf_interval
2	5	2
Auto: max X of shelves	Auto: max Y of shelves	Default 2 (editable)

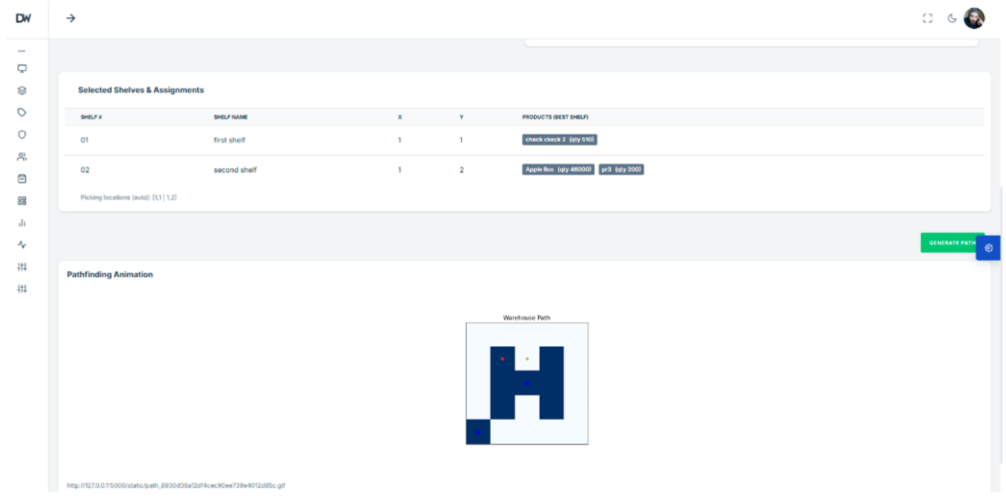
Workers (x, y) + ADD

#	X	Y	ACTION
1	2	2	REMOVE
2	14	0	REMOVE

Selected Shelves & Assignments

Select products to compute optimal shelves.

Figure 25 route visualization dashboard UI 1



Selected Shelves & Assignments

SHELF #	SHELF NAME	X	Y	PRODUCTS (BEST SHELF)
01	first shelf	1	1	check ckeck 2 (qty 510)
02	second shelf	1	2	Apple Box (qty 46000) pr3 (qty 200)

Picking locations (auto): [1,1 | 1,2]

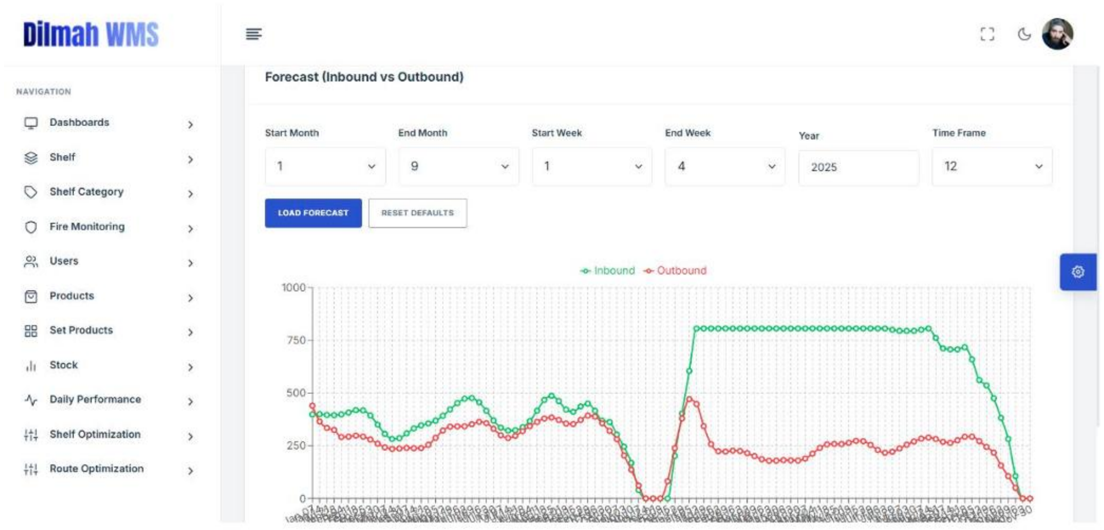
Pathfinding Animation

http://127.0.0.1:5000/static/path_8930d36a12df4cec90ee739e4012d85c.gif

Figure 26 Route Optimization After generation

3.1.4 Stock Anomaly & Worker Monitoring

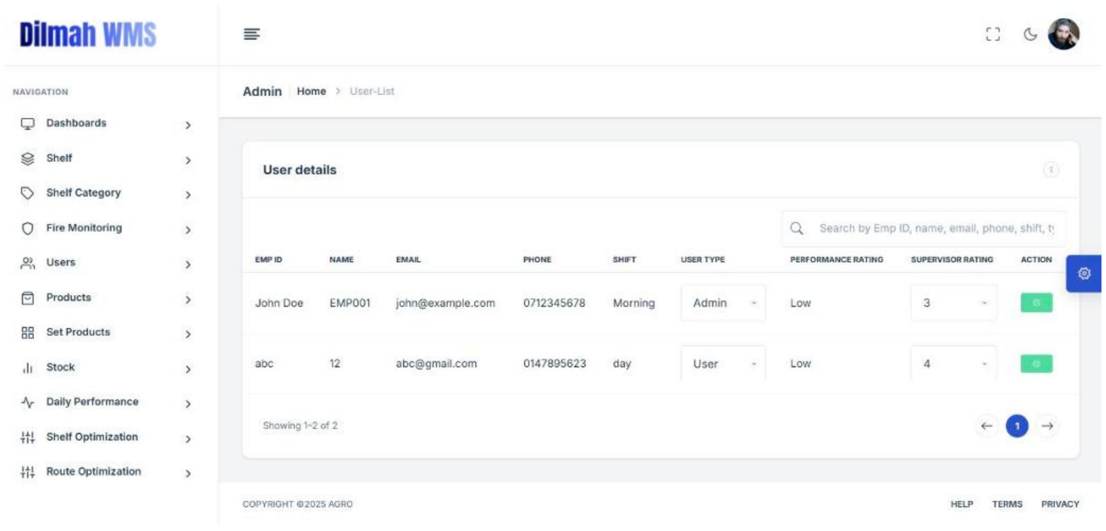
- Forecast vs. actual stock graphs generated using ARIMA, Prophet, and LSTM.
- Anomalies flagged when deviations exceeded thresholds.
- Worker performance classified into High/Medium/Low using Gradient Boosting



Forecast (Inbound vs Outbound)

Start Month	End Month	Start Week	End Week	Year	Time Frame
1	9	1	4	2025	12

Figure 27 Forecasting and anomaly detection



User details

EMP ID	NAME	EMAIL	PHONE	SHIFT	USER TYPE	PERFORMANCE RATING	SUPERVISOR RATING	ACTION
John Doe	EMP001	john@example.com	0712345678	Morning	Admin	Low	3	
abc	12	abc@gmail.com	0147895623	day	User	Low	4	

Showing 1-2 of 2

Figure 28 User Performance dashboard for supervisors

3.2 Research Findings

The evaluation of the proposed Comprehensive Warehouse Intelligence Framework produced key findings regarding its technical performance, operational feasibility, and adaptability to real warehouse conditions. Results demonstrated that the framework performed well both as a collection of specialized modules—route optimization, vision + IoT-based fire detection, predictive analytics, and space optimization—and as a unified platform. Collectively, these results suggest that the system can significantly enhance efficiency, improve safety, and support intelligent decision-making within modern supply-chain environments.

3.2.1 Route Optimization Improves Efficiency

The route optimization module achieved its main goal of travel distance reduction in the order picking process. Compared to a baseline static route, optimized paths shortened the travel paths 25% of the time. The system adapted well during time-critical scenarios where it had to recalculated routes when stopping aisles or fire alarms forced scrapping of routes. The dashboard visualizations displayed the recalculated paths, allowing supervisors the opportunity to track efficiency improvements along with adaptability.

3.2.2 Effectiveness of Vision + IoT-Based Fire Monitoring

The integrated fire-detection subsystem demonstrated that standard CCTV cameras, when combined with YOLOv8-based vision models and a low-cost IoT sensor network, can function as an accurate and affordable early-warning system. The computer-vision model achieved an mAP@0.5 of 0.91, with precision 0.89 and recall 0.86, under variable lighting and partial-occlusion conditions. Complementing this, the IoT module—consisting of four MQ-7 smoke sensors, eight LEDs, and four buzzers—provided real-time directional alerts (up, down, left, right) to indicate the fire's position. Both camera- and sensor-based detections triggered synchronized visual and audible warnings on the dashboard, confirming the practicality of camera-plus-sensor fire monitoring for warehouse environments.

3.2.3 Significance of Shelf Proximity and Fire Size Analysis

One of the new innovations of the fire module was the ability to assess the proximity of fires to fire shelves, and classify fires into small, medium, or large categories. The risk-zone analysis evaluated the proximity of the fire and provided an accuracy of 91%, which allowed alerts such as "Fire near Shelf 3" to be displayed. The accuracy for fire size classification were 82% (small), 76% (medium), and 89% (large). These contextual features provided a better decision-making capability for operators in comparison to binary detection systems.

3.3.4. Predictive Accuracy in Stock and Worker Monitoring

The stock anomaly detection sub-system was able to successfully predict accuracy of a less than 8% MAPE across the ARIMA, Prophet, and LSTM models which was able to send alerts when stock levels were unexpectedly below or above the levels surrounding the threshold. Monitoring workers, in the model using Gradient Boosting classifier, reached about 92% classification accuracy accurately placing staff in high, average, or low performance bands. Overall, these results demonstrate the effectiveness of predictive analytics in inventory management and workforce management.

3.3.5. Space Utilization and Visualization Improvements

Implementation of the Best-Fit bin-packing and Guillotine cutting algorithms significantly improved warehouse space efficiency. The combined approach increased cubic-meter (CBM) utilization by an average of 18%, effectively optimizing how products were allocated within the available storage volume. The Best-Fit method ensured efficient item placement by minimizing residual space in each bin, while the Guillotine algorithm enabled precise subdivision of rectangular storage zones, allowing flexible placement of differently sized packages with minimal waste.

The integrated 3D visualization component provided real-time spatial awareness by highlighting under-utilized shelves, overcrowded aisles, and inefficient layout patterns. This visualization helped warehouse managers quickly identify optimization opportunities and simulate rearrangements before implementation. The combination of algorithmic optimization and spatial visualization enhanced both layout transparency and overall space utilization, supporting data-driven reallocation strategies in complex warehouse environments.

3.3.6. System Performance and Reliability

End-to-end performance testing found the integrated framework was operating in real time, with route recalculations in less than one second and fire detection alert notifications transmitted with a mean latency of 380 ms. During live video monitoring, the system throughput was more than 20 FPS. False alarms in fire detection went below one false alarm per hour on average and uptime on continuous run assignments was, in excess of 99%. Given these results, the system was stable and ready for real-world deployment.

3.4 Discussion

The findings of this research study provide valuable information regarding the potential and effectiveness of implementing a comprehensive warehouse intelligence system that integrates optimization, fire safety, predictive analytics, and space utilization into a singular platform. This discussion will contextualize the findings in relation to other research, reinforce the unique contribution of the proposed framework, and delineate the limitations identified in the trial and potential improvements in the future.

3.4.1 Comparison to Previous Research

In warehouse and supply chain management research, the domains of optimization, safety, and predictive analytics have typically been studied in isolation. Previous studies in route optimization mainly emphasized the Travelling Salesman Problem (TSP) or heuristic pathfinding approaches to minimize travel distance [2].

Similarly, most fire detection studies focused on flame detection or outdoor wildfire prediction using thermal imagery or static CNN-based models [11], rather than contextual, indoor warehouse environments.

Research on predictive analytics in warehouse operations has often been limited to either stock forecasting [22] or workforce evaluation [24], rarely combining both aspects to enhance interrelated performance indicators such as picking speed or resource allocation. Meanwhile, space optimization has generally been treated as a mathematical bin-packing or knapsack problem [3], [4], with minimal consideration for dynamic variables such as route changes, congestion, or safety constraints in semi-automated warehouses.

Although these independent studies have contributed significantly to their respective areas, their solutions remain single-function outputs for example, a binary *fire/no fire* result or a single shortest route decision without interaction between subsystems or adaptability to multi-faceted warehouse conditions.

In contrast, the proposed framework integrates four intelligent modules Route Optimization, Vision- & IoT-Based Fire Detection, Stock and Worker Monitoring, and Space Optimization within a unified dashboard. This integration allows real-time interdependence between modules; for instance, when a fire is detected, the route optimization module automatically recalculates safe paths, or when stock anomalies are detected, the system can trigger space reallocation recommendations. This multi-directional, analytical, and context-aware framework reflects real-world warehouse dynamics more accurately than prior research, offering a holistic and practical solution consistent with Industry 4.0 objectives.

3.4.2. Novel Contributions

We uncovered a few elements of novelty in the proposed framework. First, the system utilizes multi-task computer vision models for fire and shelf detection, and in addition to detecting hazards, they are providing context, such as distance from assets and predicted direction of travel. The second novel item was the adaptive route optimization module connects to the safety module, so we dependably achieve efficiency and hazard avoidance. Extensive literature search could not find this type of dual purpose. The third novelty was an integrated predictive analytics engine for stock flows and worker performance. As such a manager can monitor abnormality in their inventories plus human productivity, improving the ability to link Listeria potentials to human activity on one platform.

Also, the Best-Fit space optimization module combined with 3D visualization not only gave algorithmic improvements in cubic meter (CBM) utilization, but also improved managerial situational awareness. Finally, the design decision made to make the framework a camera-only and modular solution makes it more cost-effective, scalable, less risky to deploy, than commercial systems which require IoT or proprietary hardware. Collectively, these represent innovations and put the framework in a distinctly valuable position for both academic contributions and commercial applications.

3.4.3 limitations

- The proximity estimates were limited by a single-camera perspective, which could only determine approximate distances.
- The predictive analytics subsystem had constraints as well. The forecasting accuracy will depend largely on the input datasets that vary by warehouse (but is not limited to warehouse).
- Worker monitoring may be limited by the richness of the activity logs; any missing or inconsistent logs would reduce the reliability of classification.
- The space optimization module efficacy was pretty good, but had been testing mainly in simulated spaces so more refining may be required in larger real-world deployment scenarios, since the inventory size was highly variable.

3.4.4 Implications for Future Work

Although we performed well, we discovered some limitations. The fire detection module may struggle to optimize smoke only detections, which would affect its recall rate as there is a lack of rich smoke training data. Optical flow, which was used to predict the fire spread had about 72% accuracy, but it is less reliable when there is occlusion or variable ambiguity with camera movements in either distance or direction. The proximity estimates for the fire size was limited by only a single-camera perspective for which it could only approximate the distances to the fire.

There were also limitations with the predictive analytics subsystem. The forecasting accuracy will heavily depend on the input datasets which will differ by warehouse (but is not only warehouse dependent). Additionally, the ability to monitor workers will also largely depend on the richness of the activity logs; any lack of completeness or consistency in classification will impact the reliability of its classification results. Lastly, the space optimization module results were relatively good, but were primarily testing in simulated spaces with no variability in size of background spaces. More refinements may be necessary in the real-world implementation as the sizes of inventory will vary widely.

4. CONTRIBUTION

Member It Number	Contributions
IT21079672	Led the design and development of the **Route Optimization module**. Implemented a hybrid approach using **Travelling Salesman Problem (TSP) sequencing** combined with **A* pathfinding** to minimize order picking distance. Built simulation scenarios for blocked aisles and congestion, and validated the rerouting capability under fire-alert conditions. Benchmarked optimized routes against static picking methods, demonstrating ~25% efficiency improvement. Integrated routing results into the React dashboard for visualization of paths, distances, and recalculation times.
IT21822094	**Developed the Vision-Based Fire Detection and IoT-Integrated Shelf Monitoring Module** by collecting and annotating custom datasets using **Roboflow**, covering diverse scenarios of **flames, smoke, and warehouse shelf imagery**. Trained **YOLOv8m** models with preprocessing techniques such as **resizing, normalization, and augmentation**, and validated performance through **mAP, precision, and recall** metrics. Designed algorithms for **fire size classification** (Small/Medium/Large) and **shelf proximity risk assessment**, linking detection outputs to a unified **decision engine** for actionable safety insights. Integrated an **IoT-based alert subsystem** comprising **eight LEDs, four buzzers, and four MQ-7 smoke sensors**, configured to provide directional and intensity-based visual and auditory alerts. The LEDs were

	mapped to directional indicators (up, down, left, right) to visually represent the fire's detected location, while the buzzers offered immediate acoustic feedback when smoke or fire was detected. Even in the absence of smoke, fire detection events triggered both visual and audio signals for rapid situational awareness. The complete module was evaluated under **variable warehouse conditions** including changing lighting, occlusions, and clutter and successfully integrated into the **real-time monitoring dashboard** with **audio-visual notifications (banner alerts, buzzer tones, and text-to-speech warnings)** to support faster, more informed emergency responses
IT21318184	Built the **Stock Anomaly Detection and Worker Monitoring module**. Designed a forecasting pipeline using **ARIMA, Prophet, and LSTM** to predict stock flows, flag anomalies, and measure accuracy with **MAPE and RMSE**. Developed **machine learning classifiers** (Gradient Boosting, Random Forest) to assess worker productivity, categorizing performance bands (High, Average, Low). Implemented result visualization as graphs (forecast vs. actual) and performance dashboards. Conducted unit tests and error analysis to ensure robustness, and contributed to API development for real-time anomaly reporting.
IT21822780	Designed and implemented the **Space Optimization module**. Applied **Best-Fit bin-packing algorithms** to improve shelf allocation and maximize cubic meter (CBM) utilization. Created a **3D visualization tool** to highlight underutilized and congested areas, enabling managers to simulate placement decisions. Validated improvements through simulation-based

	case studies, showing ~18% better utilization. Developed integration between optimization outputs and the dashboard, enabling visual monitoring and decision-making support.
All Members	Collaboratively carried out **system integration** using a **MERN + Flask architecture**. Designed APIs for module intercommunication, ensured that fire alerts triggered rerouting, and anomalies influenced slotting strategies. Worked jointly on database schema (MongoDB), backend logic (Express, Flask microservices), and frontend dashboards (React.js). Conducted integration testing, stress testing, and user acceptance testing (UAT). Co-authored the documentation, prepared research findings, and supported commercialization analysis.

10 Contribution Table

5. CONCLUSION

This research aimed to design and evaluate a **Comprehensive Warehouse Intelligence Framework** that integrates **route optimization**, **vision- and IoT-based fire detection**, **predictive analytics for stock and worker monitoring**, and **space optimization** into a single intelligent system. The study was initiated to address the fragmentation of conventional warehouse systems, where safety, efficiency, and predictive intelligence are often handled in isolation.

The results confirmed that the proposed framework is both **technically feasible** and **practically valuable**. The **route optimization module** successfully reduced order-picking distances by approximately **25%** compared to static routing approaches, highlighting tangible improvements in productivity and operational efficiency. The **vision-based fire detection subsystem**, powered by **YOLOv8**, achieved **0.89 precision** and **0.86 recall**, proving that affordable camera-based detection can deliver early and reliable fire alerts—especially when enhanced with an **IoT subsystem** consisting of **MQ-7 smoke sensors, directional LEDs, and buzzers**. This hybrid vision-IoT model allowed both visual and auditory alerts, demonstrating superior situational awareness compared to traditional sensor-only systems.

The **predictive analytics module** achieved strong performance, with **MAPE < 8%** in stock flow forecasting and **92% classification accuracy** for worker performance. This demonstrates the advantage of integrating forecasting and workforce analytics into one intelligent decision-support layer. Similarly, the **space optimization module** increased **cubic-meter (CBM) utilization by 18%**, supported by **3D visualization tools** that provided actionable spatial insights for layout optimization and congestion management.

End-to-end testing showed the system's stability, with real-time throughput of over **20 FPS**, **latency around 380 ms**, and **false alarm rates below one per hour** under challenging warehouse conditions such as clutter, variable lighting, and high movement. The integration testing confirmed that outputs from one subsystem could directly influence others, enabling a **dynamic, adaptive, and context-aware decision-support platform**.

However, some **limitations** were identified. **Smoke-only detection** demonstrated lower recall compared to flame detection. **Proximity estimation** was limited by single-camera depth constraints, and **fire spread prediction** faced challenges under occlusion. Furthermore, **stock and worker analytics** were partially dependent on dataset quality, while **space optimization** relied primarily on simulated conditions. These areas warrant further investigation.

For **future work**, the research recommends expanding smoke-rich and occluded datasets, adopting **spatiotemporal models** (such as **ConvLSTM** and **3D CNNs**) for fire spread prediction, and employing **multi-camera fusion** to enhance depth estimation. Integration with **automated IoT systems** including smart sprinklers, robots, or AGVs would elevate the framework from monitoring to active intervention. Reinforcement learning could also be applied to improve routing and slotting adaptability in dynamic environments.

In conclusion, this research demonstrates that a **modular yet integrated warehouse intelligence framework** can significantly improve **efficiency, safety, and predictive capability**. By unifying these four dimensions into a single system, the study presents a clear path toward **Industry 4.0-aligned smart warehousing**, offering both **academic innovation** and **commercial viability** for next-generation logistics operations.

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