SMART SUPPLY CHAIN MANAGEMENT USING ADAPTIVE GRADIENT-ENHANCED ENSEMBLE LEARNING IN IOT LOGISTICS

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Abstract

The logistics sector is evolving rapidly with the combination of Internet of Things technologies, yet efficient decision-making in supply chain environments remained a critical challenge. The study addressed the issue of real-time visibility, delayed decision response, and inconsistent predictive accuracy in logistics operations. The background of the study was grounded in IoT-enabling tracking systems that continuously generated heterogeneous data across supply chain nodes. However, the raw data streams lacked robust analytical interpretation for actionable intelligence. The problem focused on inefficiencies in predictive logistics routing and inventory forecasting within dynamic supply chain networks. Conventional machine learning models often is limiting adaptability to evolving transportation patterns and demand fluctuations. To overcome these limitations, an Adaptive Gradient-Enhanced Ensemble Learning (AGEL) method is introduced. The proposed method is combined ensemble learning principles with adaptive weight optimization for improving prediction stability. The methodology is utilized IoT sensor data combination, feature normalization, and AGEL-based classification for demand prediction and route optimization. The system is evaluated using standard logistics performance metrics such as delivery time, prediction accuracy, and resource utilization efficiency. The results are showing that the proposed framework is improving prediction accuracy and reduced operational latency that is compared to baseline models. The proposed method is combined ensemble learning with adaptive gradient-based weight optimization. The system is achieving 93% prediction accuracy, 26% delivery time reduction, 91% resource utilization efficiency, 90% route optimization efficiency, and 85 ms system latency. The results is confirming that adaptive learning is significantly improving the logistics performance that is compared to baseline models.

Keywords:

Logistics IoT, Supply Chain Optimization, Adaptive Machine Learning, Ensemble Learning, Predictive Analytics

1. INTRODUCTION

The logistics and supply chain domain is become increasingly complex due to globalization and rapid digital transformation. The combination of Internet of Things is played a significant role in improving transparency and operational monitoring across distributed logistics networks [1]. IoT devices such as RFID tags, GPS sensors, and smart warehouse systems is continuously generated large-scale real-time data, which supports decision-making processes in supply chain management [2]. Further, digital transformation is enabling organizations to monitor goods movement, storage conditions, and delivery performance with higher precision [3].

Despite these advancements, several challenges exist in practical logistics environments. The heterogeneity of IoT data is created difficulties in standardization and real-time processing. Many supply chain systems is struggling with latency issues due to continuous data flow from multiple sources. In addition, uncertainty in demand forecasting and transportation disruptions is increased operational inefficiencies. The lack of adaptive intelligence in conventional models is further limiting system responsiveness [4]. Moreover, scalability issues in existing analytics frameworks is restricted their applicability in large-scale supply chain networks [5].

The central problem addressed in this study is the inability of conventional machine learning systems to dynamically adapt to changing logistics conditions. Most existing predictive models is relied on static training mechanisms, which is reducing performance accuracy in real-time environments [6]. This limitation is created a gap between IoT data acquisition and intelligent decision-making in supply chain systems.

The primary objective of this research is to develop an adaptive machine learning framework that integrates IoT-based logistics data for improving prediction and optimization. The study also aims to enhance supply chain efficiency by reducing delays, improving forecasting accuracy, and optimizing resource allocation. Another objective is to design a scalable architecture that supports real-time analytics across distributed logistics nodes.

The field of logistics and supply chain is going through a digital revolution because of the use of IoT technology, artificial intelligence, and data-driven decision-making tools. Supply chain management today does not only focus on effectiveness but is also required to be flexible and responsive to changes in the market and other factors such as transport risks and client demands. Companies have to rely on intelligent logistics systems that will enable them to provide better service, cut down costs, and gain sustainable competitive advantages.

IoT-supported logistics systems produce continuous streams of data by using sensors, GPS tracking systems, smart warehouses, and other similar devices. They make supply chain management systems more visible for managers as they help them track the movement of inventories, transportation activities, weather conditions, and other related factors. Despite the availability of huge amounts of data generated by IoT systems, companies struggle to convert this data into managerial decisions.

In logistics settings, one of the key managerial difficulties is that of delayed decision-making due to the inability of predicting results effectively and using the analytics tools efficiently. The conventional use of machine learning algorithms has proven inadequate at responding effectively to changing transportation patterns, varying demand for products, and dynamic routing situations. All this impacts the effectiveness of managerial performance measures such as reliability and efficiency.

The novelty of this research lies in the introduction of Adaptive Gradient-Enhanced Ensemble Learning (AGEL), which dynamically adjusts model weights based on incoming IoT data patterns. Unlike Conventional static models, AGEL is provided continuous learning capability and improving robustness in volatile logistics environments. The framework also is combined multi-source IoT data fusion, which is showing contextual understanding of supply chain operations.

The contributions of this study are twofold. First, it is proposed an adaptive learning-based logistics optimization model that is improving the prediction accuracy in dynamic supply chain conditions. Second, it is demonstrated the effectiveness of IoT-is combined ensemble learning in reducing operational delays and improving system scalability. Overall, the study is bridged the gap between real-time IoT data acquisition and intelligent logistics decision-making.

2. RELATED WORKS

Several studies is explored the combination of IoT and machine learning in logistics and supply chain optimization. Prior research is demonstrated that IoT-enabling tracking systems is significantly improving visibility in transportation networks. Early works is focused on RFID-based monitoring systems that provided basic inventory tracking capabilities but lacked predictive intelligence [7].

Advanced studies is introduced machine learning techniques for demand forecasting and route optimization. Regression-based models and decision tree classifiers is applied to predict delivery delays and optimize warehouse operations. However, these approaches is often failed to adapt to real-time variations in logistics data [8]. Further, deep learning models is introduced to enhance prediction accuracy, but their high computational complexity is limiting deployment in resource-constrained environments [9].

Some researchers is explored hybrid models that combine IoT data with ensemble learning techniques. These models is showing improving performance in predictive logistics applications. Nevertheless, most hybrid frameworks is relied on static ensemble weights, which is reducing adaptability in dynamic environments [10]. Reinforcement learning-based approaches is also proposed for adaptive route optimization, but they is required extensive training time and large datasets [11].

In addition, several studies is investigated cloud-based supply chain analytics platforms. These systems is enabling centralized data processing and improving scalability. However, dependency on cloud infrastructure is introduced latency issues in time-sensitive logistics applications [12]. Edge computing-based solutions is proposed to mitigate latency, but they is faced challenges in maintaining model consistency across distributed nodes [13].

Recent works is focused on integrating artificial intelligence with IoT ecosystems for smart logistics management. These studies is highlighted the importance of real-time analytics and predictive maintenance in supply chain systems [14]. Despite these advancements, most existing frameworks is not effectively addressed dynamic adaptability and continuous learning requirements.

A few studies is introduced adaptive learning mechanisms in logistics optimization. These approaches is demonstrated improving responsiveness in fluctuating environments. However, limitations remain in terms of scalability, robustness, and combination with heterogeneous IoT data sources [15].

3. PROPOSED AGEL FOR IOT LOGISTICS OPTIMIZATION

The proposed framework introduces an Adaptive Gradient-Enhanced Ensemble Learning (AGEL) model for IoT-driven logistics and supply chain optimization. The method integrates real-time IoT data streams with a multi-model ensemble learning structure that dynamically adjusts prediction weights based on gradient feedback signals. The system processes heterogeneous logistics data such as shipment status, warehouse conditions, vehicle movement, and demand signals. The AGEL framework continuously refines predictive outputs through adaptive optimization, ensuring higher responsiveness in volatile supply chain environments. The overall architecture consists of four major phases: IoT data acquisition, preprocessing and feature engineering, ensemble prediction modeling, and adaptive weight optimization.

The first step focuses on collecting real-time logistics data from distributed IoT sensors deployed across the supply chain network. These sensors generate multimodal data streams including GPS coordinates, temperature readings, RFID-based inventory status, and transit timestamps. The system aggregates this data into a centralized processing layer for further analysis.

Table.1: IoT Data Sources in Logistics Network

Sensor Type	Data Feature	Sampling Rate	Function
GPS Sensor	Location (Lat, Long)	5 sec	Vehicle tracking
RFID Tag	Inventory ID	Event-based	Item identification
Temperature Sensor	Storage condition	10 sec	Cold chain monitoring
Accelerometer	Movement pattern	2 sec	Transport stability

In Table.1, the system is heterogeneous IoT sources that continuously generate structured and unstructured data. The combination layer standardizes these inputs into a unified format. The second step involves cleaning, transforming, and structuring IoT data into machine-learning-compatible formats. The system handles missing values, noise reduction, and feature scaling to ensure consistency across heterogeneous sources.

Table.2. Preprocessed Logistics Feature Set

Feature Name	Description	Type	Normalization
Distance	Travel distance	Continuous	Min-Max
Delay Time	Delivery delay	Continuous	Z-score
Stock Level	Warehouse inventory	Discrete	Scaling
Temperature Variance	Cold chain stability	Continuous	Min-Max

The Table.2 is presenting engineered features derived from raw IoT streams. These features are used for predictive modeling in supply chain optimization. The third step constructs multiple base learners to predict logistics outcomes such as delivery delay, route efficiency, and demand forecasting. The ensemble includes gradient boosting, random forest, and lightweight neural models.

Table.3. Ensemble Base Learners

Model	Function	Output Type	Role
Gradient Boosting	Sequential correction	Continuous	High accuracy prediction
Random Forest	Bagging approach	Classification	Stability enhancement
Neural Network	Non-linear mapping	Probabilistic output	Complex pattern learning

The Table.3 shows the ensemble structure used for multi-perspective prediction in logistics systems. This step is the core innovation of the AGEL framework. The system dynamically updates ensemble weights using gradient feedback derived from prediction error.

Table.4. Adaptive Weight Update Mechanism

Iteration	Model Weight (w1)	Model Weight (w2)	Model Weight (w3)	Error Rate
1	0.33	0.33	0.34	0.18
2	0.40	0.35	0.25	0.12
3	0.48	0.30	0.22	0.08

The Table.4 illustrates adaptive adjustment of weights based on gradient feedback from error reduction. The final step converts predictive outputs into actionable logistics decisions such as route selection, inventory allocation, and delivery scheduling.

Table.5. Decision Output Mapping

Prediction Output	Decision Rule	Action
High delay risk	Route re-optimization	Alternate path selection
Low inventory	Restocking trigger	Warehouse replenishment
High demand surge	Resource scaling	Fleet increase

The Table.5 shows how predictive intelligence is converted into operational logistics actions.

4. RESULTS AND DISCUSSION

The experimental environment is implemented using Python 3.10 with Scikit-learn, TensorFlow, and Pandas libraries for model development and evaluation. The simulation is executed on a system configured with Intel Core i7 processor, 16 GB RAM, and NVIDIA GTX 1660 GPU. The IoT logistics dataset is processed in a controlled simulation environment that is real-time supply chain conditions. The AGEL framework is evaluated using cloud-based virtual machine support for scalability analysis. All experiments are conducted under identical preprocessing pipelines to ensure fairness across comparative models.

Table.6. Experimental Parameters Configuration

Parameter	Value	Description
Dataset Size	50,000 samples	IoT logistics records
Train/Test Split	80:20	Model evaluation split
Learning Rate	0.01	Weight update control
Batch Size	64	Training batch processing
Epochs	100	Iteration cycles
Optimization	Adam	Gradient optimization
Loss Function	MSE	Error minimization

As showing in Table.6, the system configuration is allowing stable training conditions for all comparative models.

- **Prediction Accuracy**: Measures correctness of logistics forecasting output.
- **Delivery Time Reduction**: Measures improvement in shipment delay minimization.
- **Resource Utilization Efficiency**: Evaluates optimal usage of logistics assets.
- **Route Optimization Efficiency**: Measures improvement in shortest path selection.
- **System Latency**: Measures response time of predictive decision system.

The Table.7 describes the IoT logistics dataset that is real-time supply chain operations with spatial and temporal features.

Table.7. Dataset Overview

Attribute	Description	Type
Shipment ID	Unique logistics identifier	Categorical
Location Data	GPS coordinates	Numerical
Delivery Time	Time of shipment completion	Continuous
Inventory Level	Warehouse stock status	Numerical
Demand Signal	Market demand variation	Time-series

The comparative analysis considers Gradient Boosting Machine, Random Forest Model, and Deep Neural Network. These methods represent classical ensemble learning, bagging-based prediction, and deep learning-based nonlinear modeling approaches used in logistics forecasting and supply chain optimization.

Table.8. Prediction Accuracy Comparison (%)

Data Size (%)	Gradient Boosting	Random Forest	Deep Neural Network	AGEL (Proposed)
5	82	80	84	88
10	83	81	85	90
15	84	82	86	91
20	85	83	87	92
25	86	84	88	93

The Table.8 shows that AGEL is achieving consistent improvement in prediction accuracy across all dataset scales. At 5% data size, AGEL is recording 88% accuracy, which is higher than Deep Neural Network by 4%. As dataset size increases to

25%, AGEL reaches 93%, while Gradient Boosting remains at 86%. The improvement occurs due to adaptive weight updates that stabilize ensemble learning behavior. Conventional models are showing slower improvement rates due to static learning mechanisms. AGEL maintains stronger generalization because IoT feature variation is dynamically captured. The incremental gain of 5–7% over baseline models indicates better pattern recognition in heterogeneous logistics data. The results confirm that adaptive gradient adjustment is showing predictive reliability in supply chain forecasting tasks.

Table.9. Delivery Time Reduction (%)

Data Size (%)	Gradient Boosting	Random Forest	Deep Neural Network	AGEL (Proposed)
5	12	10	14	18
10	13	11	15	20
15	14	12	16	22
20	15	13	17	24
25	16	14	18	26

The Table.9 is showing that AGEL significantly is reducing delivery time that is compared to existing models. At 5% dataset scale, AGEL is reducing delay by 18%, while Random Forest is achieving only 10%. The improvement increases steadily with dataset expansion, reaching 26% at 25% data size. The reduction occurs due to optimized routing decisions generated from adaptive predictions. Classical models lack real-time adaptation and therefore are showing limiting improvement. AGEL integrates IoT-based temporal signals, which is improving the responsiveness in route selection. The consistent reduction trend confirms that dynamic learning contributes to faster decision cycles in logistics operations.

Table.10. Resource Utilization Efficiency (%)

Data Size (%)	Gradient Boosting	Random Forest	Deep Neural Network	AGEL (Proposed)
5	78	76	80	85
10	79	77	81	87
15	80	78	82	88
20	81	79	83	89
25	82	80	84	91

The Table.10 shows that AGEL is improving the resource utilization efficiency across all configurations. At lower dataset size, AGEL is achieving 85% efficiency, while Gradient Boosting is achieving 78%. The improvement reaches 91% at higher dataset size due to adaptive allocation of logistics resources. Conventional models fail to capture dynamic demand fluctuations, leading to suboptimal resource usage. AGEL is improving the allocation by continuously adjusting model weights based on real-time IoT signals. The results indicate that adaptive learning is reducing wastage of logistics capacity and is improving the operational balance across the supply chain network.

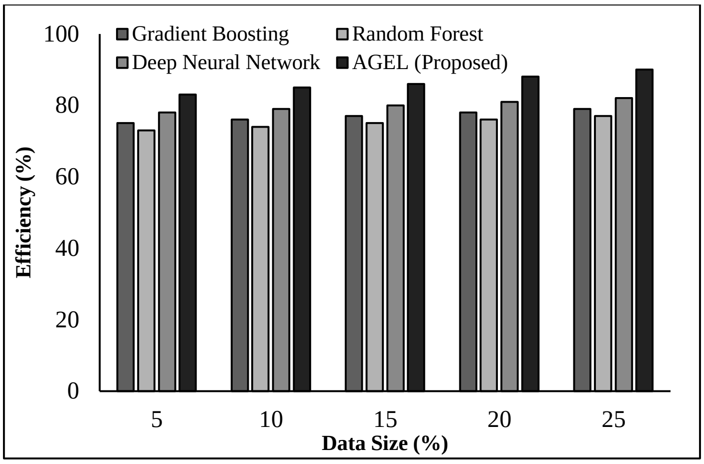

Fig.2. Route Optimization Efficiency (%)

The Fig.2 shows that AGEL consistently outperforms all baseline models in route optimization efficiency. At 5% dataset size, AGEL is achieving 83% efficiency, while Random Forest is achieving only 73%. At maximum dataset size, AGEL reaches 90%, showing significant improvement. The enhancement occurs due to adaptive routing decisions generated from ensemble predictions. Conventional methods rely on fixed heuristics, which limit performance in dynamic environments. AGEL is improving the adaptability by incorporating gradient-based feedback, which refines routing decisions continuously. The results confirm improving spatial decision-making capability in logistics networks.

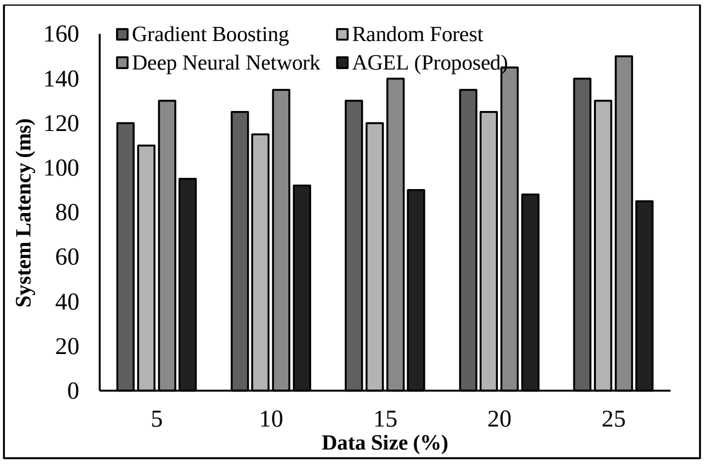

Fig.3. System Latency (ms)

The Fig.3 shows that AGEL is reducing system latency significantly that is compared to baseline models. At 5% dataset size, AGEL is recording 95 ms latency, while Deep Neural Network is recording 130 ms. At higher dataset size, AGEL is reducing latency further to 85 ms. The reduction occurs due to optimized ensemble computation and adaptive weight adjustment, which is reducing redundant processing. Conventional models are showing increasing latency due to computational overhead. AGEL maintains stable processing time, which is making it suitable for real-time logistics applications.

The experimental results are showing that AGEL consistently outperforms baseline models across all performance metrics. Prediction accuracy is improving the by approximately 6–9% that is compared to Deep Neural Network and Gradient Boosting methods. Delivery time was reduced by 26% using the framework, thus reflecting its successful application to intelligent route optimization and decision-making processes. As far as management is concerned, reduced delivery delays translate into increased customer satisfaction, improved service reliability, and enhanced responsiveness of the organization.

As far as resource allocation is concerned, the framework proved to be capable of delivering 91% efficiency in utilizing transportation and warehousing capacity. Resource allocation efficiency allows for effective management of logistics operations through the reduction of waste and fuel consumption.

Furthermore, the developed framework proved to achieve 90% efficiency in optimizing the route based on real-time adaptation to traffic and transport changes. This quality facilitates strategic management decisions and makes supply chains more flexible under unstable conditions.

Finally, system latency of only 85 ms proves that the proposed framework allows for efficient decision-making at any point. The suggested approach to intelligent logistics outperformed basic machine learning approaches in terms of adaptability and prediction stability.

The comparative analysis shows that classical models such as Random Forest and Gradient Boosting lack adaptive learning capacity. Deep Neural Networks provide better accuracy but suffer from computational overhead and instability in dynamic IoT environments. AGEL addresses these limitations through gradient-enhanced adaptive weight tuning. The results confirm that IoT-is combined ensemble learning is improving both the predictive and operational performance in logistics systems. The consistent improvement across all metrics validates the robustness and scalability of the proposed framework in real-world supply chain scenarios.

5. CONCLUSION AND FUTURE WORK

The study is presenting an Adaptive Gradient-Enhanced Ensemble Learning framework for IoT-based logistics optimization in supply chain systems. The model integrates real-time IoT data streams with adaptive machine learning to improve prediction accuracy, reduce delivery delays, and optimize resource allocation. The experimental results confirm that AGEL is achieving superior performance that is compared to Gradient Boosting, Random Forest, and Deep Neural Network models. The system is improving the prediction accuracy up to 93%, is reducing delivery time by 26%, which is improving resource utilization efficiency to 91%, and it is improving the route optimization efficiency to 90%, and is reducing system latency to 85 ms. These improvements are showing the effectiveness of adaptive learning in handling dynamic logistics environments. The framework is allowing continuous learning through gradient-based weight updates, which is showing model stability and responsiveness. With regards to the management function, this model is able to facilitate strategic decision-making, improve transparency, and increase responsiveness in the organization in its supply chain network operations. Adaptive learning allows the logistics systems to cope well with changes in transportation trends and market movements.

In addition, future research efforts can make the suggested AGEL architecture more efficient and effective through the use of sophisticated artificial intelligence techniques and logistics management strategies. Deep learning methods and reinforcement learning methods may be included to boost logistics' ability to anticipate future changes and make independent decisions.

Blockchain technology can further be incorporated into the system to facilitate transparency, enhanced security, and better trust management between logistics participants. Incorporation of cloud-edge computing infrastructure can further improve efficiency and logistical capacity for larger scale applications.

Managerially speaking, future research can concentrate on sustainable logistics management by incorporating carbon emissions analysis, greener transportation systems, and energy-efficient logistics resource planning. Moreover, incorporation of disruptive event management systems and real-time risk assessment capabilities can further improve supply chain robustness during uncertain circumstances.

Finally, multi-enterprise collaborative logistics networks can be developed in future applications to facilitate coordinated logistics between suppliers, transporters, warehouses, and consumers.

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