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A Multi-Source Data Fusion Framework for Resilient Demand Forecasting in Smart Logistics

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ABSTRACT

Smart logistics systems increasingly depend on precise demand forecasting to streamline global supply chain operations. Current industry data reveals that logistics bottlenecks impact more than 30% of global shipments, while inaccurate forecasting contributes to a 25% surge in operational expenditures. Conventional manual estimation techniques are often inadequate, as they struggle to incorporate volatile real-world variables such as fluctuating traffic patterns, IoT telemetry, and environmental shifts. This research introduces a robust data fusion framework that synthesizes IoT, traffic, and meteorological datasets to refine demand forecasting and logistics delay projections via a hybrid Classification and Regression Tree (CART) approach. The methodology initiates with a rigorous preprocessing phase where heterogeneous data streams are cleaned, normalized, and temporally synchronized. While baseline models such as K-Nearest Neighbor (KNN) and Categorical Boosting (CatBoost) offer foundational insights, they frequently overlook the intricate interdependencies inherent in multi-source data. To address these limitations, this study proposes the Tao Tree model. This architecture utilizes a Tao Tree module for hierarchical feature selection and adaptive weighting, paired with a CART module to deliver high-precision regression for demand levels and categorical delay assessments. The integrated system is deployed via a Flask-based web application, facilitating real-time data ingestion and predictive visualization. Experimental results indicate that this framework substantially elevates forecasting accuracy and operational efficiency, offering a scalable, data-driven solution for proactive supply chain management.

Keywords: Smart logistics, CART model, Machine Learning, KNN classification, CatBoost model, Tao Tree model.

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1. INTRODUCTION

In the coming years of the Internet of Things (IoT), context-awareness bridges the interconnection between the physical world and virtual computing entities and involves environment sensing, network communication, and data analysis methodologies. Advancement enables several advanced IoT applications, such as intelligent healthcare systems, smart transport systems, smart energy systems, and smart buildings. The IoT networks' unified architecture includes smart IoT-based application services and the underlying IoT sensor networks. According to the Gartner forecast, the IoT global market envisions 5.8 billion IoT-based applications by 2020, with a 21% increase from 2019. Further, the IoT market's worldwide growth is propelled by wireless networking technologies and the adoption of emerging technologies such as cloud platforms. This trend leads to a drastic increase in demand for connected IoT devices and application services. The primary objectives of IoT sensor networks includes (i) sensing the critical information from the external physical environment, (ii) the sampling of internal system signals, and (iii) obtaining meaningful information from sensor data to perform decision-making. It is to be noted that IoT-enabled applications involve a wireless sensor network (WSN). Further, these wireless sensors are randomly positioned and capable of establishing an ad hoc network without infrastructure requirements.

Fig. 1. Global IoT in logistics market overview.

2. LITERATURE SURVEY

Reis et al. [1] proposed an IoT- and AI-driven framework for secure and sustainable green mobility, leveraging multimodal data fusion to enhance traffic management, energy efficiency, and emissions reduction. Using publicly available datasets, including METR-LA for traffic flow and OpenWeatherMap for environmental context, the framework integrates machine learning models for congestion prediction and reinforcement learning for dynamic route optimization. Simulation results demonstrate a 20% reduction in travel time, 15% energy savings per kilometer, and a 10% decrease in CO_2 emissions compared to baseline methods. Krishnamurthi et al. [2] presented the data processing techniques, such as data denoising, data outlier detection, missing data imputation, and data aggregation. Further, it elaborates on the necessity of data fusion and various data fusion methods such as direct fusion, associated feature extraction, and identity declaration data fusion. They also aim to address data analysis integration with emerging technologies, such as cloud computing, fog computing, and edge computing, towards various challenges in IoT sensor networks and sensor data analysis. In summary, this is the first of its kind to present a complete overview of IoT sensor data processing, fusion, and analysis techniques.

Liu et al. [3] found that multi-source data, including sensors, social media, citizen feedback, and GIS data, face challenges such as data quality and privacy security when being fused. Data fusion algorithms are diverse and have their own advantages and disadvantages. Data analysis algorithms help urban management in areas such as spatial analysis and deep learning. Algorithm collaboration can improve decision-making accuracy and efficiency and promote the rational allocation of urban resources. In the future, algorithm development will focus on data quality, real-time deep mining, interdisciplinary research, privacy protection, and collaborative application expansion, providing strong support for the sustainable development of smart cities. Kenda et al. [4] proposed a novel framework for data fusion of a set of heterogeneous data streams. The proposed framework enriches streaming sensor data with the contextual and historical information relevant for describing the underlying processes. The final result of the framework is a feature vector, ready to be used in a machine learning algorithm. The framework has been applied to a cloud and to an edge device. In the latter case, incremental learning capabilities have been demonstrated. The reported results illustrate a significant improvement of data-driven models, applied to sensor streams. Beside higher accuracy of the models the platform offers easy setup and thus fast prototyping capabilities in real-world applications. Abduljabbar et al. [5] contributed to this objective by developing and evaluating advanced machine learning models that leverage multisource data to predict traffic patterns more effectively, allowing for the deployment of proactive measures to prevent or reduce traffic congestion and idling times, leading to enhanced eco-friendly mobility. Specifically, they evaluated the impact of multisource sensor inputs and spatial detector interactions on machine learning-based traffic flow prediction. Using a dataset of 839,377 observations from 14 detector stations along Melbourne’s Eastern Freeway, Bidirectional Long Short-Term Memory (BiLSTM) models were developed to assess predictive accuracy under different input configurations.

Tsanousa et al. [6] presented a detailed review of state-of-the-art data fusion solutions, on data storage and indexing from various types of sensors, feature engineering, and multimodal data integration. The review aims to serve as a guide for the early stages of an analytic pipeline of manufacturing prognosis. They reviewed to literature showed that in fusion and in preprocessing, the methods chosen to be applied in this sector are beyond the state-of-the-art. Existing weaknesses and gaps that lead to future research goals were also identified. AlSalehy et al. [7] proposed spatiotemporal CO patterns and builds accurate predictive models using five years (2018–2022) of data from ten monitoring stations, combined with meteorological variables. Exploratory analysis revealed distinct diurnal and moderate weekly CO cycles, with prevailing northwesterly winds shaping dispersion. Spatial correlation of CO was low (average 0.14), suggesting strong local sources, unlike temperature (0.92) and wind (0.5–0.6), which showed higher spatial coherence. Seasonal Trend decomposition (STL) confirmed stronger seasonality in meteorological factors than in CO levels. Low wind speeds were associated with elevated CO concentrations. Key predictive features, such as 3-h rolling mean and median values of CO, dominated feature importance. Sergi et al. [8] proposed different solutions to guarantee quality and freshness of food through the whole cold chain. In this regard, the use of Internet of Things (IoT)-enabling technologies and its specific branch called edge computing is bringing different enhancements thereby achieving easy remote and real-time monitoring of transported goods. Due to the fast changes of the requirements and the difficulties that researchers can encounter in proposing new solutions, the fast prototype approach could contribute to rapidly enhance both the research and the commercial sector. In order to make easy the fast prototyping of solutions, different platforms and tools have been proposed in the last years, however it is difficult to guarantee end-to-end security at all the levels through such platforms.

Lloret et al. [9] proposed approach combines traditional assessment methods with Artificial Intelligence (AI) techniques. The methodology follows a dual approach: on the one hand, surveys are conducted using specialized staff from various public entities; on the other, AI-based models (including neural networks and transformer architectures) are used to estimate the DT level of the organizations automatically. Our approach has been applied to a real-world case study involving local public administrations in the Valencian Community (Spain) and shown effective performance in assessing DT. Fatorachian et al. [10] presented a predictive analytics framework integrating digital twin technology, IoT-enabled logistics data, and cybernetic feedback loops to improve last-mile delivery accuracy, congestion management, and sustainability in smart cities. Grounded in Systems Theory and Cybernetic Theory, the framework models urban logistics as an interconnected network, where real-time IoT data enable dynamic routing, demand forecasting, and self-regulating logistics operations. By incorporating machine learning-driven predictive analytics, the study demonstrates how AI-powered logistics optimization can enhance urban freight mobility.

Bellini et al. [11] presented a certain degree of complexity in terms of their integration and management due to partial overlaps, and in most cases, they could be exploited alternatively to implement the same smart and latest innovative solutions. They offers an overview of data models, standards and their relationships. A second contribution highlights any possible exploitation of data models for implementing operational processes for city transportation management and for the feeding of simulation and optimization processes that produce other data results in other data models. Tang et al. [12] proposed a digital twin framework by integrating the smart warehouse and manufacturing with the roulette genetic algorithm for demand forecasting in the cyclical industry. They also demonstrate how this algorithm is practically implemented for forecasting the demand, sustaining manufacturing optimization, and achieving inventory optimization. We adopted a small-scale textile company case study to demonstrate the proposed digital framework in the warehouse and demonstrate the results of demand forecasting and inventory optimization. Various scenarios were conducted to simulate the results for the digital twin.

Syed et al. [13] provided a holistic coverage of the Internet of Things in Smart Cities. We start by discussing the fundamental components that make up the IoT based Smart City landscape followed by the technologies that enable these domains to exist in terms of architectures utilized, networking technologies used as well as the Artificial Algorithms deployed in IoT based Smart City systems. This then followed up by a review of the most prevalent practices and applications in various Smart City domains. Mohsen et al. [14] proposed an innovative framework that integrates artificial intelligence (AI), autonomous vehicles (AVs), and Internet of Things (IoT) technologies to address these challenges. The framework leverages real-time data from IoT-enabled infrastructure to optimize route planning, enhance traffic signal control, and enable predictive demand management for delivery services. By incorporating AI-driven analytics, the proposed approach aims to improve traffic flow, reduce congestion, and minimize the carbon footprint of urban logistics, contributing to the development of more sustainable and efficient smart cities. Zaman et al. [15] conducted an analysis of the scientific literature on the application of the Internet of Things (IoT) and artificial intelligence (AI) in enhancing supply chain operations. They applies a dual approach combining bibliometric analysis and topic modeling to explore both quantitative citation trends and qualitative thematic insights. By examining 810 qualified articles, published between 2011 and 2024, this research aims to identify the main topics, key authors, influential sources, and the most-cited articles within the literature. The study addresses critical research questions on the state of IoT and AI integration into supply chains and the role of these technologies in resolving digital supply chain management challenges.

3. PROPOSED METHODOLOGY

The proposed algorithm introduces a novel hybrid data fusion framework that integrates IoT, traffic, environmental, and logistics data to perform simultaneous demand forecasting and logistics delay prediction. Unlike traditional or existing methods surveyed in the

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literature, which rely either on single-source historical data or conventional ML models, this approach combines tree-based ensemble learning, KNN predictions, and customized feature weighting to exploit correlations across multiple heterogeneous datasets. For classification, the model fuses the outputs of CatBoost and TaoTree classifiers, with environmental and traffic variables receiving higher importance through dynamic feature weighting. For regression, TaoTree regression and scaled KNN predictions are used, enhanced by preprocessing techniques that standardize, encode, and normalize features, ensuring robust handling of missing or noisy data. This integrated method is designed to overcome the drawbacks of existing approaches, such as low prediction accuracy, lack of multi-source data integration, and delayed reactive decision-making, by providing a real-time, adaptive, and highly accurate predictive system. The proposed algorithm also supports single-point and batch predictions, making it suitable for practical deployment in smart logistics environments.

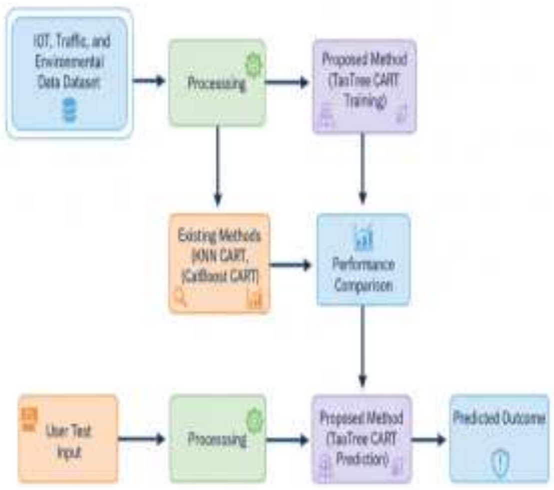

Fig. 2. Proposed system architecture.

Step 1: Dataset Collection and Integration: The research begins with the collection of multi-source datasets, including IoT sensor readings for asset utilization and inventory levels, traffic condition data, environmental measurements like temperature and humidity, and logistics operational data such as shipment status and user transactions. By integrating these heterogeneous sources, the system captures both spatial and temporal variations in demand and potential delays, providing a rich foundation for predictive modeling.

Step 2: Data Preprocessing: Preprocessing ensures the dataset is clean, consistent, and machine-readable. Missing values are handled using imputation techniques or domain-specific defaults to avoid biases. Categorical variables, including asset IDs, traffic conditions, shipment status, and logistics delay reasons, are transformed into numerical values through label encoding, enabling models to process them effectively. Continuous features are standardized using StandardScaler, which ensures all variables contribute proportionally during model training. Outliers and anomalies are identified and treated to reduce noise, enhancing model stability and predictive performance.

Step 3: Existing Model Building: As a baseline, traditional models are trained, including KNN CART, CatBoost CART, and TaoTree CART models, separately for classification (logistics delay) and regression (demand forecasting). This step allows comparison with the proposed methodology and helps highlight improvements in accuracy and efficiency. Hyperparameters are tuned, and models are evaluated using standard metrics to ensure robust performance on unseen test data.

Step 4: Proposed Model Building: The proposed framework combines multiple machine learning approaches in a novel manner. For classification, a weighted ensemble of CatBoost and TaoTree classifiers is applied, with dynamic feature importance adjustments based on traffic and environmental conditions. For regression, predictions from TaoTree regression and KNN

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regression are fused, creating an optimized output that captures non-linear dependencies in demand fluctuations. The novelty lies in cross-source data fusion, ensemble integration, and dynamic feature weighting, which have not been explored in existing surveys. This ensures superior accuracy, robustness, and adaptability to changing conditions in smart logistics.

Step 5: Performance Evaluation: The models are evaluated comprehensively. Classification performance is measured using accuracy, precision, recall, and F1-score, while regression models are assessed with RMSE, R^2 score, MAE, and MSE. Visualizations such as predicted vs actual plots, residual analysis, and confusion matrices are used to interpret model behavior and identify areas for improvement. This evaluation confirms that the hybrid approach outperforms traditional methods in both predictive accuracy and resilience.

Step 6: Prediction on New Unseen Data: Finally, the system is deployed for predictions on unseen data. Both single-point predictions and batch predictions are supported, enabling stakeholders to anticipate demand changes and potential logistics delays in real time. Categorical outputs are mapped into interpretable labels (e.g., “Yes”/“No” for delays), while regression outputs provide precise numeric demand forecasts. This practical deployment demonstrates the real-world utility of the proposed methodology, offering predictive insights that drive proactive, data-driven logistics management.

4. Results Description

Fig. 3 displays the user interface system; an advanced machine learning platform designed for supply chain management. It leverages data from IoT-enabled assets to perform two primary functions: demand forecasting and logistics delay prediction. To achieve this, the platform integrates various data sources, including inventory levels, environmental conditions, and traffic status. It employs a dual-model approach, using regression models like KNN and CatBoost for predicting future demand levels and classification models such as Naive Bayes and CatBoost to assess the probability of delays. The interface allows users to perform EDA on the sensor and supply chain data, compare the performance of different machine learning models, and ultimately make single or batch predictions using real-time data or uploaded files.

Fig. 4 displays the dashboard provides a high-level statistical and structural summary of the dataset used for model training. It begins with a Dataset Overview, indicating that the dataset contains 4000 rows (data points) and 16 columns (features), with a total of 1052 missing values that require preprocessing. The Dataset Features section explicitly lists the variables, which include temporal data (Timestamp), identifiers (Asset_ID), logistical metrics (Inventory_Level, Traffic_Status), sensor readings (Temperature, Humidity), and the target variables (Demand_Forecast, Logistics_Delay). Finally, the dashboard initiates the visualization process by displaying the distributions of the two primary target variables—Demand Forecast (likely for regression analysis) and Logistics Delay (for classification analysis)—to help understand their underlying patterns and frequencies.

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Fig. 3. UI dashboard for an IoT demand forecasting system.

Fig. 4. EDA dashboard for the IoT demand forecasting system.

Fig. 5 displays the section that visually analyzes the two target variables for the machine learning models. On the left, a histogram displays the demand forecast distribution, revealing the frequency of different forecast values, which range from approximately 100 to 300. This continuous distribution confirms that demand forecasting is a regression problem. On the right, a bar chart shows the logistics delay distribution, which is a binary variable with two classes: 0 (No delay) and 1 (Yes, delay). This visualization indicates that predicting logistics delay is a classification problem and also highlights the class distribution, showing more instances of delays (1) than non-delays (0) within the dataset.

Fig. 5. Target variable distribution section of EDA dashboard.

Fig. 6 displays a classification performance comparison dashboard for predicting logistics delays in an IoT supply chain system. It compares three machine learning models—KNN, CatBoost, and TaoTree—across accuracy, precision, recall, and F1-score metrics. TaoTree achieves perfect scores (1.00) in all metrics, while KNN scores around 0.92 for accuracy and precision, and CatBoost performs the lowest (~0.807 accuracy, ~0.805 F1-score). The upper section presents individual model results with icons, and the lower bar chart visually contrasts the four metrics across models using color-coded bars (blue for accuracy, orange for precision, green for recall, red for F1-score).

Fig. 7 displays the dashboard, which provides a comparative analysis of three machine learning models such as KNN Regressor, CatBoost Regressor, and TaoTree Regressor—

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used for demand forecasting. The performance of each model is evaluated using four standard regression metrics: Root Mean Squared Error (RMSE), R^2 Score, Mean Absolute Error (MAE), and Mean Squared Error (MSE). According to the results, the TaoTree Regressor demonstrates superior performance, achieving the lowest error values (RMSE: 0.12, MAE: 0.07) and the highest R^2 score (0.958), indicating it has the best predictive accuracy and fit for the dataset. In contrast, the CatBoost Regressor performs poorly, while the KNN Regressor shows fair results. The bar charts at the bottom offer a direct visual comparison, reinforcing the conclusion that the TaoTree model is the most effective for this specific forecasting task.

Fig. 8 displays the user interface that allows for making real-time predictions by manually entering feature values for a single data instance. The Prediction Configuration section at the top lets the user select the prediction type (e.g., 'Single Input'), the model type (likely 'Regressor' for demand or 'Classifier' for delay), and the specific algorithm to use (e.g., TaoTree Regressor). Below, the Enter Feature Values section contains input fields organized into logical groups such as Asset Information (Asset ID, Asset Utilization), Location & Inventory (Latitude, Longitude, Inventory Level), Shipment & Traffic (Shipment Status), and Environmental Conditions (Temperature, Humidity). Once these input features are populated, the system will process them through the selected trained model to generate a prediction for either demand forecast or logistics delay.

Fig. 6. Regression performance comparison dashboard.

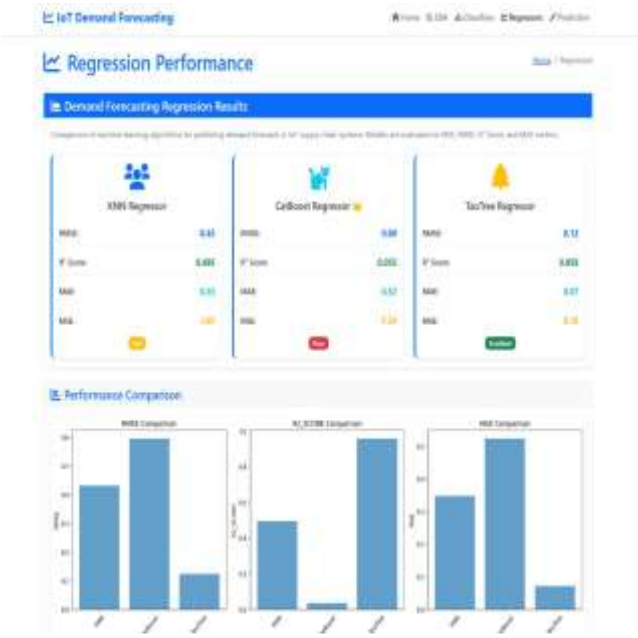

Fig. 7. Regression performance comparison dashboard.

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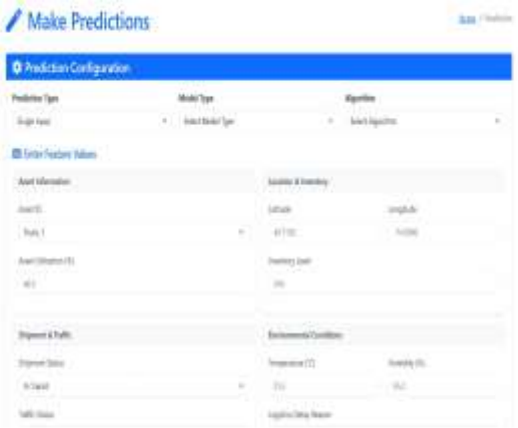

Fig. 8. Prediction input interface for the IoT demand forecasting system.

Fig. 9. Prediction execution and results interface.

Fig. 9 displays the interface, which is the operational component of the application where users can apply the trained machine learning models to new data. The Prediction Configuration panel allows the user to select the prediction mode (e.g., single or batch), the type of model (classifier or regressor), and the specific algorithm. After clicking "Make Prediction," the system processes the input data. The Batch Prediction Results section displays the output in a tabular format, showing the original input features for each instance (like Asset_ID, Temperature, and Traffic_Status) along with the model's predictions. This allows for the analysis of multiple predictions at once, and the "Download CSV" functionality enables the user to export these results for reporting or use in other downstream systems.

5. CONCLUSION

The system successfully integrates IoT, traffic, and environmental data to provide accurate demand forecasting and logistics delay predictions for smart logistics operations. By leveraging multiple machine learning algorithms including KNN, GaussianNB, CatBoost, and TaoTree, the system demonstrates robust performance for both regression and classification tasks. The modular design of the Flask framework ensures seamless interaction between data preprocessing, model training, prediction, and visualization components. The inclusion of exploratory data analysis enables users to gain insights into dataset distributions, feature correlations, and potential bottlenecks in logistics operations. Additionally, the batch prediction functionality allows for efficient large-scale forecasting, while single prediction functionality provides quick decision support. Overall, the system enhances operational efficiency, reduces uncertainties in logistics planning, and enables data-driven decision-making by providing interpretable and reliable results through a user-friendly web interface.

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