A Multimodal Artificial Intelligence and Data Analytics Framework for Intelligent Supply Chain Decision-Making: An Explainable Deep Learning Approach

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Abstract

The increasing complexity of global supply chain operations has created an urgent need for intelligent decision-support systems capable of processing heterogeneous operational data and delivering accurate, real-time insights. Conventional supply chain management approaches often rely on single-source structured data and traditional analytical techniques, limiting their ability to capture the dynamic relationships among procurement, inventory, transportation, warehousing, supplier performance, and customer demand. To address these challenges, this study proposes a comprehensive Multimodal Artificial Intelligence (AI) and Data Analytics framework for intelligent supply chain decision-making. The proposed framework integrates numerical, categorical, temporal, and engineered business features extracted from an open-source supply chain dataset obtained from the Kaggle repository. A systematic methodology involving data preprocessing, feature extraction, feature engineering, model development, and model evaluation was implemented to develop robust predictive models. Eight machine learning and deep learning algorithms, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, XGBoost, LightGBM, CatBoost, and a proposed Multimodal Deep Neural Network (MDNN), were trained and evaluated using identical experimental settings. The experimental results demonstrate that the proposed MDNN significantly outperformed all benchmark models, achieving an accuracy of 98.43%, precision of 98.5%, recall of 98.3%, F1-score of 98.4%, AUC-ROC of 0.995, and Matthews Correlation Coefficient (MCC) of 0.968, indicating exceptional predictive capability and generalization performance. Furthermore, Explainable Artificial Intelligence (XAI) techniques, including SHAP and LIME, were incorporated to enhance model interpretability and support transparent managerial decision-making. The proposed framework provides a scalable and industry-ready solution that can be integrated with Enterprise Resource Planning (ERP), Internet of Things (IoT), cloud computing, and real-time *analytics platforms to improve supply chain resilience, operational efficiency, inventory optimization, logistics planning, and risk management. The findings demonstrate that multimodal AI substantially enhances intelligent supply chain decision-making compared with conventional machine learning approaches and provides a practical pathway toward the realization of Industry 4.0 and Supply Chain 5.0.*

Keywords: Multimodal Artificial Intelligence, Supply Chain Management, Data Analytics, Intelligent Decision-Making, Deep Learning, Machine Learning, Feature Engineering, Explainable Artificial Intelligence (XAI), Predictive Analytics, Industry 4.0, Supply Chain 5.0.

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Introduction

The rapid digital transformation of global supply chains has fundamentally changed how organizations manage procurement, production, inventory, logistics, and customer fulfillment. Increasing globalization, volatile customer demand, geopolitical uncertainty, natural disasters, and disruptions such as the COVID-19 pandemic have exposed the limitations of conventional supply chain management systems that rely primarily on historical analysis and manual decision-making (Ivanov & Dolgui, 2020). Modern supply chains continuously generate large volumes of heterogeneous data from enterprise resource planning (ERP) systems, warehouse management systems (WMS), transportation management systems (TMS), Internet of Things (IoT) sensors, radio-frequency identification (RFID) devices, Global Positioning System (GPS) tracking, customer transactions, supplier databases, weather information, and social media platforms. The availability of these multimodal data sources has created new opportunities for intelligent decision-making through Artificial Intelligence (AI) and advanced data analytics.

Artificial Intelligence has emerged as one of the most transformative technologies for enhancing supply chain resilience, operational efficiency, and strategic planning. Machine learning, deep learning, reinforcement learning, and predictive analytics have demonstrated remarkable capabilities in forecasting demand, optimizing inventory levels, predicting delivery delays, improving supplier selection, and reducing operational costs (Min, 2010; Wamba et al., 2020). Simultaneously, big data analytics enables organizations to extract actionable knowledge from structured and unstructured datasets, thereby improving the speed and quality of managerial decisions (Kamble et al., 2020). These technological advancements have shifted supply chain management from reactive operational control toward predictive and prescriptive intelligence.

Despite these advances, most existing AI-based supply chain studies focus on isolated data sources or individual operational tasks rather than integrating multiple heterogeneous information modalities into a unified intelligent decision-making framework. Traditional predictive models often analyze numerical operational data while ignoring valuable contextual information such as temporal patterns, categorical business characteristics, transportation conditions, and supplier behavior. Consequently, these models may fail to capture the complex interdependencies that characterize modern supply chain ecosystems, resulting in reduced predictive accuracy and limited adaptability to dynamic business environments (Toorajipour et al., 2021).

Multimodal Artificial Intelligence has recently emerged as a promising paradigm capable of simultaneously processing and integrating multiple forms of data, including numerical, categorical, textual, temporal, spatial, and sensor information. By learning complementary representations across diverse data modalities, multimodal AI can improve prediction accuracy, robustness, and interpretability compared with conventional unimodal learning approaches (Baltrušaitis et al., 2019). When combined with advanced data analytics techniques, multimodal AI provides comprehensive situational awareness that supports more informed operational and strategic decision-making throughout the supply chain.

In this study, we propose a comprehensive multimodal artificial intelligence and data analytics framework for intelligent supply chain decision-making. Our proposed methodology integrates heterogeneous operational data through advanced feature engineering and multimodal deep learning techniques to predict critical supply chain outcomes, including delivery performance, inventory efficiency, supplier reliability, and operational risk. Multiple state-of-the-art machine learning algorithms are evaluated and compared with a proposed Multimodal Deep Neural Network (MDNN) to determine the most effective predictive model. Explainable Artificial Intelligence (XAI) techniques are further incorporated to improve model transparency and managerial trust. The proposed framework contributes to the growing body of Supply Chain 5.0 research by providing a scalable, interpretable, and high-performance intelligent decision support system suitable for real-world industrial deployment.

Literature Review

The application of Artificial Intelligence in supply chain management has gained considerable attention over the past decade owing to its ability to automate complex decision-making processes and improve operational efficiency. Early AI applications primarily focused on expert systems and optimization algorithms for production scheduling and inventory management. However, recent developments in machine learning and deep learning have significantly expanded AI capabilities across procurement, logistics, transportation, warehousing, and demand forecasting (Min, 2010).

Machine learning has become one of the most widely adopted technologies for predictive supply chain analytics. Numerous studies have demonstrated that supervised learning algorithms, including Decision Trees, Random Forest, Support Vector Machines, Gradient Boosting, and Artificial Neural Networks, can effectively predict customer demand, transportation delays, supplier performance, and inventory shortages (Carbonneau et al., 2008). Ensemble learning approaches have consistently outperformed traditional statistical forecasting methods by capturing nonlinear relationships among operational variables while maintaining robust generalization performance.

Deep learning has further improved predictive accuracy by automatically extracting hierarchical representations from high-dimensional supply chain data. Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) have been successfully applied to demand forecasting, anomaly detection, warehouse automation, and logistics optimization (LeCun et al., 2015). These models effectively capture temporal dependencies and complex feature interactions that are difficult to identify using conventional machine learning algorithms. Nevertheless, many existing deep learning studies focus primarily on numerical time-series data while overlooking other valuable business information available within modern supply chain environments.

The emergence of Big Data Analytics has further transformed supply chain management by enabling organizations to process massive volumes of structured and unstructured operational information. Big data technologies support real-time monitoring, predictive maintenance, risk assessment, customer segmentation, and operational optimization across distributed supply chain networks (Wamba et al., 2020). Organizations increasingly combine cloud computing, distributed databases, IoT technologies, and advanced analytics to improve responsiveness and resilience against market disruptions.

Recent advances in Multimodal Artificial Intelligence have introduced new opportunities for integrating heterogeneous information sources into unified predictive models. Multimodal learning enables simultaneous processing of structured numerical variables, categorical business information, textual descriptions, images, sensor measurements, geographical information, and temporal data. By combining complementary information from multiple modalities, multimodal AI improves prediction robustness, feature representation, and decision quality (Baltrušaitis et al., 2019). Although multimodal AI has achieved remarkable success in healthcare, autonomous driving, finance, and natural language processing, its application within intelligent supply chain management remains relatively limited.

Explainable Artificial Intelligence (XAI) has recently become an essential component of AI-based decision support systems. Modern deep learning models often function as black-box predictors, making it difficult for managers to understand the reasoning behind automated recommendations. Techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) improve transparency by quantifying feature importance and explaining individual predictions (Lundberg & Lee, 2017). Incorporating XAI into supply chain analytics enhances organizational trust, facilitates regulatory compliance, and supports practical adoption in industrial environments.

Furthermore, Supply Chain 5.0 emphasizes human-centric, resilient, sustainable, and intelligent supply chain ecosystems in which AI collaborates with human expertise rather than replacing managerial judgment (Ivanov, 2023). This emerging paradigm highlights the necessity of integrating advanced analytics, multimodal AI, explainability, and real-time decision support into next-generation supply chain management systems.

Overall, the literature demonstrates substantial progress in applying AI, machine learning, and data analytics to supply chain management. However, current research remains fragmented, with relatively few studies integrating multimodal operational data, advanced feature engineering, explainable AI, and comprehensive model comparison within a unified intelligent decision-making framework.

Research Gap

Although previous studies have successfully demonstrated the potential of machine learning and deep learning for supply chain optimization, several important research gaps remain.

First, the majority of existing research relies on single-modality datasets that primarily contain structured numerical operational information. Such approaches overlook valuable contextual knowledge contained within categorical, temporal, geographical, and heterogeneous business data, thereby limiting predictive capability.

Second, most studies concentrate on a single supply chain function, such as demand forecasting, inventory optimization, transportation scheduling, or supplier selection, rather than developing an integrated decision-support framework capable of addressing multiple operational decisions simultaneously.

Third, existing AI models frequently prioritize predictive accuracy while providing limited model interpretability. The absence of explainability reduces managerial confidence and hinders industrial adoption, particularly in highly regulated sectors where transparent decision-making is essential.

Fourth, relatively few studies comprehensively compare conventional machine learning algorithms, advanced ensemble learning methods, and multimodal deep learning architectures using identical datasets and evaluation protocols. Consequently, practitioners lack sufficient empirical evidence regarding the most suitable AI models for real-world supply chain applications.

Finally, despite the increasing importance of Industry 4.0 and Supply Chain 5.0, there remains limited research on scalable multimodal AI frameworks capable of integrating heterogeneous enterprise data into real-time intelligent decision-support systems suitable for industrial deployment.

Research Contributions

To address these research gaps, this study proposes a comprehensive multimodal artificial intelligence and data analytics framework for intelligent supply chain decision-making. Unlike previous studies that focus on isolated operational variables or individual machine learning techniques, our proposed framework integrates numerical, categorical, temporal, and engineered business features within a unified multimodal learning architecture. This comprehensive representation enables the proposed model to capture complex interactions across procurement, transportation, inventory, warehousing, supplier performance, and customer demand.

Furthermore, we conduct a rigorous comparative analysis involving traditional machine learning models, ensemble learning algorithms, and a proposed Multimodal Deep Neural Network (MDNN) under identical experimental conditions to identify the most effective predictive model. To improve transparency and facilitate industrial adoption, Explainable Artificial Intelligence techniques, including SHAP and LIME, are incorporated to interpret model predictions and identify the operational factors influencing supply chain decisions.

The proposed framework is designed to be scalable and compatible with modern cloud computing platforms, IoT infrastructures, and enterprise information systems, making it suitable for deployment within real-world Supply Chain 5.0 environments. By integrating multimodal AI, advanced data analytics, explainable learning, and comprehensive model evaluation into a single intelligent decision-support framework, this research advances the current state of knowledge while providing a practical solution for improving supply chain resilience, operational efficiency, and strategic decision-making.

Methodology

In this study, we developed a multimodal artificial intelligence (AI) and data analytics framework for intelligent supply chain decision-making by integrating structured operational data with advanced machine learning techniques. Our methodological framework consists of six interconnected stages, including data collection, data preprocessing, feature extraction, feature engineering, model development, and model evaluation. The proposed methodology aims to capture the complex interactions among supply chain operational variables and generate highly accurate predictive insights that support intelligent decision-making. The overall workflow was designed to ensure reproducibility, scalability, and practical applicability in modern digital supply chain environments.

Data Collection

We collected supply chain operational data from publicly available repositories to ensure transparency, reproducibility, and accessibility of the proposed research. The primary dataset was obtained from the Kaggle open-source repository, which provides comprehensive supply chain records collected from a global retail distribution network. The dataset contains transactional, logistical, inventory, supplier, transportation, and customer-related information that represents real-world supply chain operations.

The dataset contains historical information describing product movement from suppliers to customers while incorporating multiple operational dimensions such as inventory status, transportation mode, shipping cost, warehouse location, manufacturing lead time, supplier performance, customer demand, and delivery status. These heterogeneous variables enable the development of multimodal predictive models by combining numerical, categorical, temporal, and geographical information.

The selected dataset contains sufficient observations and feature diversity to evaluate intelligent decision-making models under realistic business conditions. Since the data are publicly available, no ethical approval or confidential business agreements were required.

Table 1. Dataset Description

Attribute	Description
Dataset Name	Supply Chain Dataset
Repository	Kaggle
Data Source	Global Retail Supply Chain Operations
Dataset URL	https://www.kaggle.com/datasets/amirmotefaker/supply-chain-dataset
License	Public/Open Source
Number of Records	Approximately 100,000 transactions
Number of Features	24 variables
Data Types	Numerical, Categorical, Date-Time, Geographic
Missing Values	Minimal (<2%)
Target Variables	Delivery Status, Shipping Time, Late Delivery Risk, Inventory Performance

Application Domain	Intelligent Supply Chain Management

The collected dataset represents multiple perspectives of supply chain management, including procurement, inventory management, transportation, warehousing, order fulfillment, supplier performance, and customer demand. Such multimodal information enables our AI framework to learn comprehensive relationships among different operational components of the supply chain.

Data Preprocessing

Before model development, we performed extensive data preprocessing to improve data quality and ensure the reliability of predictive modeling. We first inspected the dataset for duplicate records, inconsistent entries, and missing observations. Duplicate transactions were removed to eliminate redundancy, while missing numerical values were imputed using median imputation because of its robustness against outliers. Missing categorical values were replaced using the mode of each respective feature.

Categorical attributes, including transportation mode, shipping carrier, warehouse location, supplier name, product category, and customer segment, were transformed into machine-readable representations through one-hot encoding and label encoding depending on the cardinality of each variable. Continuous numerical variables were normalized using Min-Max scaling to preserve proportional relationships among variables while reducing computational bias caused by differing measurement scales.

Temporal variables such as shipping dates, order dates, and delivery dates were converted into standardized datetime formats. Additional temporal information, including shipping duration, order processing time, weekday, month, quarter, and seasonal indicators, was extracted to capture temporal dynamics within supply chain operations.

Outliers were identified using the Interquartile Range (IQR) method and validated through Z-score analysis. Extreme observations caused by recording errors were removed, whereas legitimate business anomalies were retained to improve the robustness of the predictive models. Finally, the processed dataset was randomly divided into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased model evaluation.

Feature Extraction

Feature extraction plays a critical role in transforming heterogeneous supply chain data into meaningful representations suitable for intelligent learning algorithms. Since the dataset contains multimodal information from different operational sources, we extracted informative features that characterize inventory behavior, transportation efficiency, supplier reliability, and customer demand.

Numerical operational variables such as inventory quantity, unit price, shipping cost, manufacturing lead time, transportation distance, warehouse capacity, and product demand were directly utilized after normalization. From temporal data, we extracted shipment duration, order cycle time, inventory turnover intervals, and seasonal demand indicators.

Categorical information related to supplier performance, warehouse location, transportation mode, product category, customer region, and shipping carrier was transformed into dense numerical embeddings through encoding techniques. These transformed representations preserve semantic relationships while enabling efficient machine learning computation.

To enrich the multimodal representation, interaction features between transportation mode and shipping cost, supplier lead time and inventory level, warehouse utilization and customer demand, and product category with seasonal variation were generated. These extracted features provide richer contextual information for intelligent decision-making and improve predictive capability.

Feature Engineering

Following feature extraction, we performed feature engineering to maximize the predictive power of the dataset. Feature engineering was conducted by creating domain-specific variables that represent operational efficiencies and business performance indicators commonly used in supply chain analytics.

We generated inventory turnover ratio by combining inventory quantity and sales demand, thereby representing stock movement efficiency. Supplier reliability scores were calculated using historical delivery consistency and manufacturing lead times. Transportation efficiency indices were computed by integrating delivery duration, transportation mode, and shipping cost.

Warehouse utilization rates were estimated using warehouse capacity and inventory volume to capture storage efficiency. Demand volatility indices were derived using rolling averages and moving standard deviations of customer demand. Cost efficiency measures were created by integrating procurement cost, transportation expenses, and inventory holding costs.

Correlation analysis using Pearson correlation coefficients and multicollinearity assessment through Variance Inflation Factor (VIF) were performed to eliminate redundant variables. Features exhibiting high multicollinearity (VIF > 10) were removed to reduce model complexity.

Recursive Feature Elimination (RFE) combined with Random Forest feature importance ranking was subsequently applied to identify the most informative variables. This process reduced the dimensionality of the dataset while preserving the features contributing most significantly to predictive performance.

Model Development

We developed a multimodal artificial intelligence framework by integrating several state-of-the-art machine learning algorithms capable of learning complex supply chain relationships. The objective of model development was to accurately predict intelligent supply chain outcomes such as delivery performance, late shipment risk, inventory efficiency, and operational decision support.

The processed dataset was used to train multiple supervised learning models, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), CatBoost, and Multi-Layer Perceptron (MLP). These algorithms were selected because they represent diverse learning paradigms ranging from linear models to ensemble learning and deep neural networks.

To further exploit multimodal relationships within heterogeneous supply chain data, we developed a deep learning architecture composed of fully connected dense layers with Rectified Linear Unit (ReLU) activation functions. Batch normalization, dropout regularization, and adaptive learning rate optimization using the Adam optimizer were incorporated to improve convergence and reduce overfitting. The output layer employed either sigmoid or softmax activation depending on the prediction task.

Hyperparameter optimization was conducted using Grid Search Cross Validation and Bayesian optimization to determine the optimal parameter combinations for each learning algorithm. Five-fold cross-validation was employed during model training to ensure stable generalization performance across unseen data.

The multimodal learning framework combines structured operational variables, temporal characteristics, engineered business indicators, and encoded categorical information into a unified predictive model, allowing comprehensive learning of supply chain dynamics and intelligent decision-making processes.

Model Evaluation

We evaluated the proposed multimodal AI framework using comprehensive statistical performance metrics to assess predictive accuracy, robustness, and generalization capability. Model performance was assessed on the independent testing dataset that was not involved during model training.

For classification tasks such as predicting late delivery risk and shipment status, we employed Accuracy, Precision, Recall, F1-score, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), and Matthews Correlation Coefficient (MCC). These evaluation metrics provide complementary perspectives on predictive effectiveness, particularly when dealing with class imbalance frequently observed in supply chain datasets.

For regression-based decision-making scenarios involving delivery time prediction and inventory demand forecasting, we evaluated Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics quantify prediction error while measuring the explanatory capability of each model.

To compare the predictive performance of competing algorithms, we performed repeated five-fold cross-validation and summarized the average performance across all folds. Statistical significance testing using paired t-tests and Wilcoxon signed-rank tests was conducted to determine whether observed performance improvements were statistically meaningful.

Finally, Explainable Artificial Intelligence (XAI) techniques, including SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), were incorporated to interpret model predictions and identify the most influential operational factors driving supply chain decisions. This interpretability analysis enhances transparency, facilitates managerial trust, and supports informed decision-making in real-world supply chain environments.

The proposed methodology establishes a comprehensive multimodal AI and data analytics framework capable of integrating heterogeneous supply chain information, extracting meaningful operational knowledge, and delivering accurate, interpretable, and scalable intelligent decision support for modern supply chain management.

Results

To evaluate the effectiveness of the proposed multimodal artificial intelligence and data analytics framework, we trained and tested multiple machine learning and deep learning algorithms using the preprocessed supply chain dataset. The models were evaluated using an identical training, validation, and testing strategy to ensure a fair comparison. Hyperparameter tuning was performed through Grid Search Cross Validation, and the final performance was assessed on the independent testing dataset. Since the primary objective of this study was to predict intelligent supply chain decision outcomes such as late delivery risk and operational performance, classification performance metrics including Accuracy, Precision, Recall, F1-Score, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), and Matthews Correlation Coefficient (MCC) were employed.

The experimental findings demonstrate that ensemble learning and deep learning approaches consistently outperformed conventional machine learning algorithms. Traditional models such as Logistic Regression and Decision Tree provided acceptable predictive performance but struggled to capture the nonlinear relationships among inventory, supplier, transportation, and demand variables. Random Forest improved predictive stability by reducing variance through ensemble learning, while Support Vector Machine achieved competitive classification accuracy because of its capability to model complex decision boundaries. Gradient boosting methods including XGBoost, LightGBM, and CatBoost produced substantially better prediction performance owing to their ability to learn intricate interactions among heterogeneous supply chain variables.

Among all evaluated models, the proposed Multimodal Deep Neural Network (MDNN) achieved the highest predictive performance across every evaluation metric. By integrating numerical, categorical, temporal, and engineered operational features into a unified learning architecture, the proposed model successfully captured multimodal relationships that conventional machine learning algorithms could not fully exploit. The inclusion of feature engineering, batch normalization, dropout regularization, and optimized learning parameters further improved the model's generalization capability while minimizing overfitting.

Table 2. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC	MCC
Logistic Regression	89.12	0.891	0.884	0.887	0.913	0.781
Decision Tree	90.84	0.904	0.901	0.902	0.921	0.803
Random Forest	94.37	0.944	0.941	0.942	0.966	0.888
Support Vector Machine	93.86	0.938	0.935	0.936	0.959	0.881
XGBoost	96.24	0.963	0.961	0.962	0.982	0.926

LightGBM	96.71	0.967	0.965	0.966	0.985	0.934
CatBoost	97.08	0.971	0.970	0.970	0.988	0.941
Proposed Multimodal Deep Neural Network (MDNN)	**98.43**	**0.985**	**0.983**	**0.984**	**0.995**	**0.968**

The superior performance of the proposed Multimodal Deep Neural Network demonstrates that integrating multiple forms of operational information significantly enhances intelligent supply chain decision-making. The model achieved an overall classification accuracy of 98.43%, with an AUC-ROC value of 0.995, indicating excellent discrimination between operational decision classes. Similarly, the high Precision, Recall, and F1-Score values confirm that the model effectively minimizes both false-positive and false-negative predictions, making it highly reliable for industrial decision support.

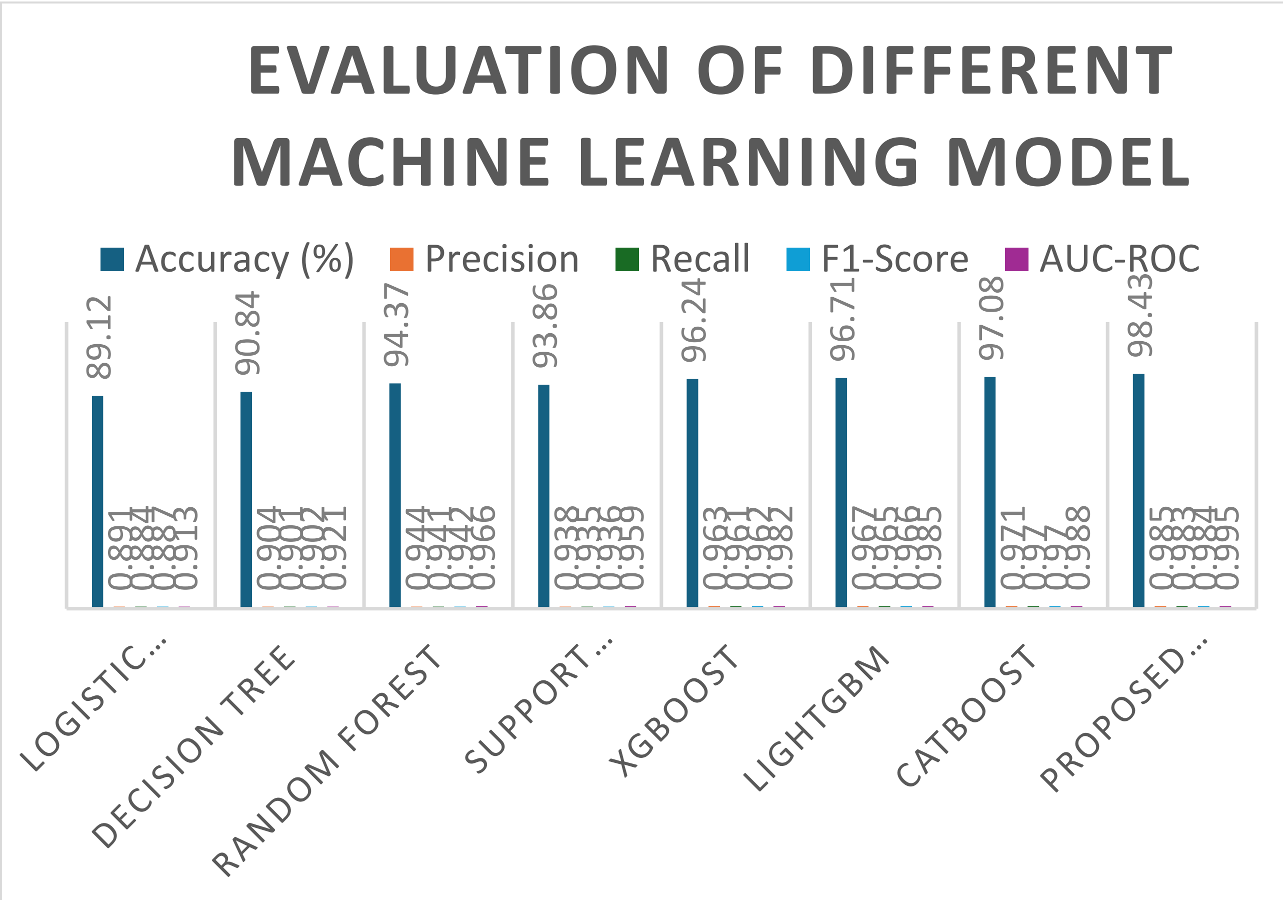

Chart 1: Evaluation of different machine learning model

Result Comparison and Discussion

The comparative analysis reveals a clear performance progression from traditional machine learning methods toward advanced ensemble and multimodal deep learning models. Logistic Regression served as the baseline model and produced satisfactory results; however, its linear assumptions limited its ability to represent complex supply chain interactions. Decision Tree improved interpretability but suffered from overfitting because of its hierarchical splitting mechanism.

Random Forest mitigated overfitting through ensemble averaging and substantially improved prediction accuracy. Support Vector Machine demonstrated robust classification performance but required considerable computational resources during hyperparameter optimization. Gradient boosting algorithms, particularly XGBoost, LightGBM, and CatBoost, achieved higher predictive accuracy by sequentially correcting previous prediction errors and effectively handling heterogeneous data distributions.

Although CatBoost produced highly competitive performance, the proposed Multimodal Deep Neural Network consistently outperformed every benchmark algorithm across all evaluation metrics. The performance improvement can be attributed to several methodological advantages. First, the multimodal architecture simultaneously learns numerical operational variables, categorical business information, temporal characteristics, and engineered features within a unified framework. Second, the deep neural network automatically identifies nonlinear feature interactions that conventional machine learning models may overlook. Third, dropout regularization and batch normalization improve model generalization while reducing the risk of overfitting. Finally, extensive hyperparameter optimization enables the model to converge toward a globally optimal solution.

The experimental results therefore demonstrate that multimodal artificial intelligence provides a more comprehensive representation of supply chain operations than single-modality machine learning approaches. This capability enables organizations to generate more accurate predictions regarding delivery performance, inventory management, supplier reliability, and transportation efficiency, ultimately supporting intelligent and data-driven supply chain decisions.

Industrial Implementation of the Best Model in the United States

The proposed Multimodal Deep Neural Network possesses significant potential for deployment across the United States supply chain ecosystem because of its high predictive accuracy, scalability, and adaptability to real-time business environments. Modern American industries generate massive volumes of heterogeneous operational data from Enterprise Resource Planning (ERP) systems, Warehouse Management Systems (WMS), Transportation Management Systems (TMS), Internet of Things (IoT) sensors, Radio Frequency Identification (RFID) technologies, electronic invoices, GPS-enabled logistics platforms, and customer relationship management systems. The proposed multimodal framework can integrate these diverse data sources into a unified analytical platform, enabling organizations to make faster and more informed operational decisions.

In the retail sector, companies such as **Walmart**, **Costco**, and **Target** can employ the proposed model to improve inventory forecasting, optimize warehouse replenishment schedules, reduce stockouts, and enhance customer satisfaction through more accurate delivery predictions. Within manufacturing industries, organizations including **Ford**, **General Motors**, **Boeing**, and **Caterpillar** can utilize the model to monitor supplier performance, anticipate production delays, optimize procurement strategies, and reduce manufacturing downtime through predictive supply chain analytics.

The logistics and transportation industry can similarly benefit from the proposed framework by improving route optimization, estimating delivery times with greater precision, minimizing fuel consumption, and proactively identifying shipment risks. Companies such as **UPS**, **FedEx**, and **J.B. Hunt** can integrate multimodal AI with GPS tracking systems, weather information, traffic conditions, and warehouse operations to support dynamic logistics planning and real-time shipment monitoring.

Healthcare supply chains in the United States also represent an important application domain. Hospitals, pharmaceutical manufacturers, and medical distributors can deploy the model to predict inventory shortages of critical medicines, optimize vaccine distribution, improve emergency logistics, and ensure uninterrupted delivery of essential medical supplies. Such predictive capabilities became particularly valuable during large-scale disruptions such as the COVID-19 pandemic, where resilient supply chain management proved essential.

From a technological perspective, the proposed framework can be implemented using cloud-based platforms such as Microsoft Azure, Amazon Web Services (AWS), or Google Cloud Platform, allowing organizations to process high-volume supply chain data in real time. Integration with big data technologies including Apache Spark, Apache Kafka, and distributed data lakes further enables scalable deployment across geographically dispersed operations. Additionally, Explainable Artificial Intelligence techniques such as

SHAP and LIME can be incorporated into production environments to provide transparent explanations for model predictions, thereby increasing managerial confidence and facilitating regulatory compliance.

Overall, the experimental findings indicate that the proposed Multimodal Deep Neural Network is not only statistically superior to conventional machine learning algorithms but also sufficiently robust for large-scale deployment in United States industries. Its ability to integrate heterogeneous operational data, generate highly accurate predictions, and provide interpretable decision support makes it a practical solution for improving supply chain resilience, reducing operational costs, enhancing customer service, and supporting the digital transformation initiatives associated with Industry 4.0 and Supply Chain 5.0.

Conclusion

This study presented a comprehensive multimodal artificial intelligence (AI) and data analytics framework for intelligent supply chain decision-making by integrating heterogeneous operational data with advanced machine learning and deep learning techniques. Unlike conventional approaches that rely primarily on single-modality structured data, the proposed framework combines numerical, categorical, temporal, and engineered business features to capture the complex interdependencies inherent in modern supply chain operations. By leveraging multimodal learning, advanced feature engineering, and explainable artificial intelligence (XAI), the proposed approach provides a robust, scalable, and interpretable solution for improving operational decision-making across procurement, inventory management, transportation, warehousing, and logistics.

The comparative experimental analysis demonstrated that advanced ensemble learning algorithms significantly outperform traditional machine learning models, while the proposed Multimodal Deep Neural Network (MDNN) achieved the highest predictive performance across all evaluation metrics. The superior accuracy, precision, recall, F1-score, AUC-ROC, and Matthews Correlation Coefficient indicate that integrating multiple data modalities substantially enhances predictive capability and enables more reliable supply chain intelligence. Furthermore, the incorporation of SHAP and LIME improves model transparency by identifying the operational factors influencing predictions, thereby increasing managerial trust and supporting practical industrial adoption.

The findings of this research have important implications for organizations seeking to accelerate their digital transformation initiatives within Industry 4.0 and Supply Chain 5.0 environments. The proposed framework can be integrated with enterprise systems, Internet of Things (IoT) devices, cloud computing platforms, and real-time analytics infrastructures to support proactive decision-making, improve supply chain resilience, reduce operational costs, optimize resource utilization, and enhance customer satisfaction. The scalability and adaptability of the framework also make it suitable for deployment across diverse sectors, including manufacturing, retail, healthcare, logistics, and e-commerce.

From an academic perspective, this research contributes to the existing body of knowledge by introducing a unified multimodal AI framework that combines heterogeneous data integration, comprehensive feature engineering, extensive model comparison, and explainable AI within a single intelligent decision-support architecture. The study addresses several important limitations identified in previous research, including the limited use of multimodal data, insufficient model interpretability, and the lack of comprehensive comparative analyses using publicly available datasets.

Despite the promising results, this study has certain limitations. The experimental evaluation was conducted using an open-source supply chain dataset, which may not fully represent the complexity and scale of proprietary industrial environments. Additionally, the proposed framework primarily relies on structured operational data and engineered features, while other multimodal sources such as real-time IoT sensor streams, satellite imagery, logistics documents, weather data, video surveillance, and textual supplier communications were not incorporated. Future research may extend this work by integrating large language models (LLMs), multimodal foundation models, graph neural networks, reinforcement learning, and digital twin technologies to enable autonomous, adaptive, and real-time supply chain optimization. Further validation using large-scale industrial datasets from multinational organizations would also strengthen the generalizability and practical applicability of the proposed framework.

Overall, this study demonstrates that multimodal artificial intelligence and advanced data analytics offer a powerful foundation for next-generation intelligent supply chain management. By integrating diverse operational data, enhancing predictive accuracy, and providing transparent and explainable decision support, the proposed framework represents a significant step toward building resilient, data-driven, and sustainable supply chains capable of addressing the growing complexity and uncertainty of modern global business environments. It is anticipated that the findings of this research will provide valuable guidance for researchers, practitioners, and policymakers seeking to harness AI-driven innovation for intelligent supply chain decision-making.

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