AI-Driven Intelligence in Logistics: A Multiclass Shipment Status Classification

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Monalisha Pattnaik
G Mariam Rao
Ratan Kumar Behera
Laxmi Priya Panda
Umrah Naushad
Sambalpur University
(monalisha_1977@yahoo.com)
(mariamrao94@gmail.com)
(ratankb21@gmail.com)
(laxmipriyapanda.1992@gmail.com)

In the evolving landscape of supply chain and logistics management, intelligent data utilization is critical for optimizing delivery performance, asset utilization, and operational efficiency. This study presents a comprehensive AI and machine learning pipeline applied to real-world logistics data involving shipment tracking performance metrics. We implement a multiclass classification model approach for predictive modeling. Classification models Random Forest, XGBoost accurately predict shipment outcomes. This AI-Driven intelligence framework delivers actionable insights for logistics managers, enabling data-driven decisions, improved customer satisfaction, and reduced operational costs. Results demonstrate significant potential for applying AI to enhance resilience, adaptability, and sustainability in transportation systems.

Keywords: AI, Logistics, Multiclass Classification, Predictive Modeling, Shipment Tracking

1. Introduction

The integrity of data is crucial for enhancing AI-driven shipment tracking systems' accuracy, as high-quality data significantly influences the predictive capabilities of AI models; thus, literature suggests that AI-powered data quality management systems utilize machine learning and automation to perpetually enhance data reliability, optimizing processing workflows while minimizing human intervention (Shah et al., 2024). Within the logistics field, the integration of AI technologies markedly enhances operational effectiveness by utilizing real-time analytics and autonomous systems that are contingent upon precise and trustworthy data for superior performance (Adenuga et al., 2024). The implementation of AI-based data quality checks in regulated landscapes highlights the urgent requirement to sustain data correctness, all-encompassing nature, and consistency to meet compliance standards and elevate operational performance (Tomar et al., 2024). Furthermore, the progress in artificial intelligence and machine learning has facilitated logistics systems in forecasting disruptions and enhancing routing efficiency, reliant on superior data quality (Rane et al., 2024). In the cargo sector, contemporary recurrent neural network frameworks have been utilized to markedly enhance data integrity, thus improving the precision of shipment monitoring and forecasting models (Wong et al., 2020). The merging of Internet of Things and blockchain within logistics emphasizes the essential nature of data integrity, given that these advancements depend on exact, well-rounded, and timely information to ensure transparency and foster stakeholder confidence (Ahmed et al., 2021). Innovative architectures that consistently monitor and validate data authenticity across decentralized networks emphasize the value of upholding high-quality data metrics to guarantee the trustworthiness of real-time insights and automated choices. The synthesis of these studies underscores that data quality is essential for the precision and efficacy of AI-driven shipment tracking systems, as it supports analytical accuracy, operational efficiency, and the reliability of decision-making in logistics (Shah et al., 2024). AI-enhanced intelligence markedly improves the precision of shipment status classification in logistics through the application of sophisticated machine learning algorithms and real-time data processing, with models like Extreme Gradient Boosting (XGBoost) achieving up to 99.92% accuracy in training datasets, thus highlighting their efficacy in optimizing shipment tracking systems (Özdemir et al., 2024). AI technologies, notably computer vision and deep learning, play a crucial role in the accurate classification of parcel conditions, achieving damage detection accuracy rates as high as 98.8%, thus enhancing quality control and consumer satisfaction(Chaudhary & Singh, 2024). Furthermore, AI-driven predictive analytics and autonomous systems enhance operational efficiency by reducing human error and improving delivery times(Rane et al., 2024)(Adenuga et al., 2024). The use of convolutional neural networks (CNN) and long short-term memory (LSTM) networks in smart logistics systems further refines parcel classification, achieving detection accuracies of up to 98.52% for specific parcel weights(Sharma et al., 2023). These AI applications not only improve the accuracy of shipment status classification but also contribute to cost reduction, enhanced customer satisfaction, and increased supply chain resilience(didast et al., 2024)(Fatorachian, 2024). However, challenges such as data security, regulatory compliance, and system integration need to be addressed to fully realize the potential of AI in logistics(Kumar, 2025)(Ajayi, 2025). Overall, AI-driven intelligence is transforming logistics by providing more accurate, efficient, and reliable shipment status classification, which is crucial for maintaining competitive advantage in the global market(Adenuga et al., 2024). Moreover, the deployment of digital twins and predictive maintenance tools within logistics networks ensures continuous monitoring and adaptation, thereby improving the reliability of shipment status predictions(Adenuga et al., 2024). The use of ensemble-based regression algorithms, such as Random Forest and Gradient Boosting, also contributes to improved generalization error and classification accuracy in predicting delivery delays(Rezki & Mansouri, 2024). Finally, the application of Shapley values in analyzing data feature contributions provides insights into optimizing prediction models, which can enhance the accuracy of shipment status classification by identifying and leveraging the most impactful data features(Zhang & Qi, 2023). Collectively, these factors underscore the importance of advanced algorithm selection, real-time data integration, and feature analysis in achieving high accuracy in AI-driven shipment status classification. By creating and assessing different artificial intelligence (AI) and machine learning (ML) models targeted at the multiclass classification of logistic shipment status, this study aims to address the crucial problem of data imbalance.The investigation will assess the efficacy of an array of models, including “Multinomial Logistic Regression (MLR)”, “Support Vector Machine (SVM)”, “Artificial Neural Networks (ANN)”, Random Forest (RF)”, “Decision Tree (DT)”, “XGBoost, and “K-Nearest Neighbour (K-NN)”. In order to determine the best models and methods for creating a high-performing logistic shipment status can precisely classify and predict, this study will analyze and compare these different methodologies.

The aforementioned AI and ML fraud detection strategies are based on the analyzed research. The remaining sections of the chapter are arranged as follows: a literature review is conducted in Section 2. The datasets for Section 3 are introduced, along with the necessary data analysis. The comprehensive elucidation of the artificial intelligence and machine learning frameworks is delineated in Section 4. Section 5 elucidates the empirical assessment and outcomes pertaining to all the frameworks. The discoveries, practical ramifications, and summative observations are thoroughly addressed in Section 6.

2. Literature Review

AI- and ML-based predictive models have substantially improved shipment time accuracy from 62.91% to 93.5%, marking a 48.62% enhancement in logistics performance (Mariappan et al., 2023). AI technologies are transforming logistics and supply chain management (SCM) by promoting data-driven decision-making, automating workflows, and supporting human expertise rather than replacing it (Boute& Udenio, 2022). The integration of AI, ML, and blockchain strengthens digital supply chains through enhanced transparency, secure product tracking, and counterfeit prevention in pharmaceutical logistics (Gupta et al., 2022). Machine learning and blockchain together enhance SCM efficiency, transparency, and fraud mitigation, fostering more reliable logistics networks (Islam et al., 2023). An AI-enabled sustainable SCM model optimizes vehicle routing and load capacity, improving logistics distribution efficiency in B2C e-commerce (Qi et al., 2023). AI and ML technologies optimize capacity, reduce operational costs, improve efficiency, and enhance safety in logistics operations (Kumar et al., 2022). AI improves SCM across planning, sourcing, production, and delivery by increasing forecasting precision, product quality, and cost efficiency (Pham & Bris, 2025). AI enhances sustainable logistics by enabling real-time analytics, resource optimization, and improved environmental performance (Chen et al., 2024). AI strengthens SCM resilience through improved transparency, agile procurement, and disruption mitigation, especially during crises such as COVID-19 (Modgil et al., 2022). Machine learning and data analytics predict shipment latency, reduce operational costs, and improve supply chain responsiveness and efficiency (Aoufi & Haloua, 2025). Integrating industrial IoT and AI in vehicular logistics improves routing, real-time monitoring, and system performance by up to 98% (Bhargava et al., 2022). AI and ML models detect irregular transactions and fraudulent behavior, enhancing financial security in supply chain operations (Lokanan & Maddhesia, 2024). AI enhances SCM by improving efficiency, lowering costs, and elevating customer satisfaction, though challenges persist regarding data quality and privacy (Goswami et al., 2024). IoT-based supply chain systems enhanced with deep learning improve disaster-related risk prediction, achieving up to 94% accuracy via hybrid CNN–BiGRU models (Alzahrani & Asghar, 2023). AI-driven ML classifiers, particularly Random Forest, enable delivery risk prediction with over 93% accuracy, strengthening logistics decision-making (Al Khaldy et al., 2025). A deep learning framework combining SOM, PCA, and ANN achieves 96% accuracy in forecasting and enhances model transparency through SHAP interpretability (Ahmed et al., 2025). AI’s role in SCM spans network design, supplier selection, inventory and demand planning, and green SCM, with bibliometric analysis revealing five core thematic clusters (Sharma et al., 2022). AI advances SCM and bioinformatics by optimizing logistics, forecasting demand, and accelerating genomic research and drug discovery (Didwania et al., 2025). Machine learning enhances supply chain agility and sustainability through improved forecasting, logistics optimization, and reduced inventory errors (Pasupuleti et al., 2024). Finally, AI and ML strengthen pharmaceutical supply chain resilience by improving transparency, predictive modeling, and ethical operations, despite gaps in regulatory adoption (Al-Hourani & Weraikat, 2025).

The integration of these cutting-edge techniques into shipment status classification modeling frameworks has the potential to greatly improve the forecasting skills needed to combat the issues facing the logistics tracking system. The literature that was reviewed serves as the basis for the creation of methods such as "MLR", “SVM", "ANN", "RF", "DT", “XGBoost” and "K-NN" models for shipment classification and prediction, which augment the proficiency in early identification and classification of logistics activities.

3. Dataset Information

The dataset castoff in this study, obtained from the “Kaggle” repository “(https://www.kaggle.com/datasets/ziya07/smart-logistics-supply-chain-dataset)”. This dataset provides real-time data for smart logistics operations, capturing various aspects of supply chain management over the past year (2024). It includes information on asset tracking, inventory levels, shipment status, environmental conditions, traffic, and user behaviors. The dataset features multiple stakeholders within the logistics network, including asset IDs, timestamps, traffic conditions, waiting times, and reasons for delays. Additionally, the data is enriched with real-time information from IoT sensors, such as temperature, humidity, and asset utilization, to facilitate advanced logistics optimization and decision-making. The target variable, shipment status, helps in identifying shipment tracking in logistics processes, and the input features are "temperature, humidity, traffic status, waiting time, user purchase frequency, logistics delay reason, asset utilization and demand forecast" which is essential for enhancing supply chain efficiency through proactive management and optimization techniques. This dataset is designed to be used for research and machine learning applications focused on smart logistics and supply chain performance improvement. In total, the dataset comprises 1000 observations and 8 variables and one multiclass target variable "shipment status" representing potential risk or causal factors associated with shipment tracking. The "shipment status" variable is categorical and used as the dependent variable in model training, while the 8 measurement variables serve as independent explanatory features for the AI–ML models. Table 1 presents the descriptive statistics for these variables, and Figure 1 illustrates the correlation structure among the structures associated with "shipment status".

Table 1 *Information about Data*

SlNo	Variable	Information	Category	Coding
1	Timestamp	Date and time when the data was recorded, representing logistics activity	-	-
2	Asset_ID	Unique identifier for the logistical assets (e.g., trucks)	-	-
3	Latitude & Longitude	Geographical coordinates of the asset for tracking and monitoring	-	-
4	Inventory_Level	Current level of inventory associated with the asset or shipment	-	-
5	Shipment_Status (Target)	Status of the shipment	Delayed/Delivered/In Transit	0-2
6	Temperature (Input)	Temperature recorded at the time of the shipment or transportation	-	-
7	Humidity (Input)	Humidity level at the time of recording	-	-
8	Traffic_Status (Input)	Current traffic condition	Clear/Detour/Heavy	0-2
9	Waiting_Time (Input)	Time spent waiting during the logistics process (in minutes)	-	-
10	User_Transaction_Amount	Monetary amount associated with user transactions	High/Medium	1-2
11	User_Purchase_Frequency (Input)	Frequency of purchases made by the user	-	-
12	Logistics_Delay_Reason (Input)	Reason for any delays in the logistics process	Mechanical/None/Traffic/Weather	0-3
13	Asset_Utilization (Input)	Percentage of asset utilization, indicating how effectively assets are being used	-	-
14	Demand_Forecast (Input)	Predicted demand for the logistics services in the coming period	-	-
15	Logistics_Delay	Binary variable indicating whether a logistics delay occurred	No Delay/Delay	0-1

Table 2 *Descriptive Statistics of the Variables of Shipment Status Classification*

Sl. No.	Variables	Variable Types	Min	Q1	Median	Mean	Q3	SD	Max	Skewness	Kurtosis
1	Shipment_Status	Int	0.000	0.000	1.000	0.962	2.000	0.813	2.000	0.069	1.517
2	Temperature	Num	18.00	21.20	23.80	23.89	26.60	3.322	30.00	0.015	1.931
3	Humidity	Num	50.00	57.20	65.20	65.04	72.40	8.754	80.00	-0.054	1.798
4	Traffic_Status	Int	0.000	0.000	1.000	0.999	2.000	0.809	2.000	0.002	1.526
5	Waiting_Time	Int	10.00	23.00	35.00	35.06	49.00	14.478	60.00	0.006	1.792
6	User_Purchase_Frequency	Int	1.000	3.000	6.000	5.513	8.000	2.935	10.000	-0.003	1.712
7	Logistics_Delay_Reason	Int	0.000	1.000	2.000	1.536	3.000	1.119	3.000	-0.019	1.638
8	Asset_Utilization	Num	60.00	69.47	79.25	79.60	89.42	11.631	100.00	0.044	1.767
9	Demand_Forecast	Int	100.0	144.0	202.0	199.3	251.2	59.921	300.0	-0.017	1.692

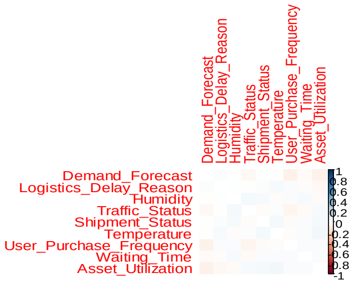

Figure 1*The Correlation Plot among the Variables Associated with "Shipment Status"*

4. Methodology

The proposed chapter employs AI and ML techniques like "Multinomial Logistic Regression", "Support Vector Machine", "Artificial Neural Network", "Random Forest", "Decision Tree", "XGBoost", and "K-Nearest Neighbour" models enabling training for multiclass classification and prediction model for shipment tracking. All of the models under study perform worse than the proposed Random Forest and XGBoost models.

4.1 Multinomial Logistic Regression

Multinomial logistic regression Multinomial logistic regression is a statistical tool of modelling associations among a nominal dependent variable that comprises of more than two categories and a number of independent variables. It operates by approximating the likelihood of a membership of a specific class with the help of the logistic function, which makes it useful in multiclass contexts in diverse areas such as health, social science, and finance (Denisko, 2018).

4.2 Support Vector Machines

Support Vector Machines are supervised learning models that are intended to discover an optimum separating hyperplane, which maximizes the space between classes. SVMs are useful in linear and nonlinear classification and can be very accurate in text, bioinformatics as well as picture recognition (Cortes and Vapnik, 1995).

4.3 Artificial Neural Networks

Artificial Neural networks consist of a network of interconnected nodes that process information by means of weighted connections. ANNs are effective in learning nonlinear, highly complicated decision boundaries during classification, and are therefore useful in speech, and image (Staudenmayer et al., 2009).

4.4 Random Forest

Random Forest is an ensemble algorithm which builds several decision trees based on bootstrap samples as well as random feature selection. Majority vote is used in making the final prediction thereby increasing accuracy and decreasing overfitting. Random forest has recorded good results in classification tasks in a wide variety of applications (Breiman, 2001).

4.5 Decision Tree

A decision tree splits data into branches, depending on the thresholds of feature values, which are terminated by class labels in the leaves. Trees are understandable and easy to interpret in order to do a simple classification, decision analysis, and variable selection (Ying, 2015).

4.6 XGBoost

XGBoost (Extreme Gradient Boosting) is a high-performance ensemble technique that uses gradient-boosted decision trees. It uses progressive construction of trees to rectify the mistakes of the previous trees and uses regularization to regulate the complexity of the model. XGBoost finds a lot of application in machine learning competitions and in real-world prediction tasks (Chen and Guestrin, 2016; Wiens, 2025).

4.7 K-Nearest Neighbours

K-nearest neighbours (K-NN) is an instance-based, non-parametric algorithm that comes up with a classification of the points basing on the most frequent classification of the k-closest points. KNN is characterized by the ability to be flexible in terms of modeling the complicated boundaries of decisions, albeit being computationally expensive on large amounts of data (Charbuty and Abdulwahab, 2021).

5. Experimental Evaluation and Results of AI-ML Models for Multiclass Classification and Prediction of the Shipment Status

It is a stimulating mission to identify the key factors of the "shipment status". The present study is focused on AI-based prediction and multiclass classification of the shipment tracking using AI and ML-based "Multinomial Logistic Regression", "Support Vector Machine", "Artificial Neural Network", "Random Forest", "Decision Tree", "XGBoost", and "K- Nearest

Neighbour" models. It is seen that, the "Random Forest" and "XGBoost" models are outperformed to the other AI-ML based models.

5.1 AI-ML Models for Multiclass Classification

In this context, using multiclass classification models, the total dataset is used for training. This methodology has been established to scrutinize the impact of all 8 variables on the classification and prediction of shipment status. Table 3 delineates the accuracy metrics in percent for the training datasets, which are recorded as [39.9, 48.7, 47.9, 100.0, 45.3, 100.0, 63.7], applying "Multinomial Logistic Regression", "Support Vector Machine", "Artificial Neural Network", "Random Forest", "Decision Tree", "XGBoost", and "K- Nearest Neighbour" models respectively for the classification and prediction of shipment tracking instances. Figure 2 shows the variable importance of 8 key inputs obtained through RF model to predict and classify the shipment status.

5.2 Decision Tree Model for Multiclass Classification

The Decision Tree (DT) model constitutes a hierarchical tree-structured classifier that elucidates the interrelationship between input variables and a target variable that is categorical.

In the context of predictive analytics, the terminal nodes of the tree yield the anticipated class subsequent to the application of a sequence of decision rules. In the present investigation, the total dataset comprising 1000 observations with 8 input variables was taken as "100% training" for the purpose of multiclass classification. The DT model was constructed utilizing the "rpart" package in R software, with "class" selected as the criterion for splitting. The performance of the model was appraised through the error rate, and the optimal tree was derived with 5 salient predictors, specifically "Asset Utilization", "Waiting Time", "Demand Forecast", "Temperature", and "Traffic Status" which collectively resulted in the minimum error. Nine internal and ten terminal nodes make up the final DT, which is shown in Figure 3, which classifies the data according to these 5 variables. According to the categorization rules, shipments with asset utilization values less than 69 and waiting time is less than 19 then status is classified as "delayed". Shipments with asset utilization values less than 69 and waiting time is greater than or equal to 19 then status is classified as "delivered". Shipments with asset utilization values greater than or equal to 69 and demand forecast is less than 111 then status is classified as "delayed". Shipments with asset utilization values greater than or equal to 69 and demand forecast is lying between 111 and 130 then status is classified as "delivered". Shipments with asset utilization values greater than or equal to 69, demand forecast is greater than or equal to 182 and temperature is less than 25 then status is classified as "delayed". Shipments with asset utilization values greater than or equal to 88, demand forecast is greater than or equal to 182 and temperature is greater than or equal to 25 then status is classified as "in transit". Shipments with asset utilization values is lying between 69 and 88, demand forecast is greater than or equal to 182 and temperature is greater than or equal to 25 then status is classified as "delivered". Shipments with asset utilization values is lying between 69 and 92, demand forecast is lying between 130 and 182 and traffic status is equal to 1 then status is classified as "delayed". Shipments with asset utilization values is greater than or equal to 92, demand forecast is lying between 130 and 182 and traffic status is equal to 1 then status is classified as "delivered". Shipments with asset utilization values is greater than or equal to 69, demand forecast is lying between 130 and 182 and traffic status is not equal to 1 then status is classified as "in transit". This partitioning process persists until the dataset is subdivided into 10 distinct segments, yielding predicted classifications of [0, 1, 0, 1, 0, 2, 1, 0, 1] based solely upon the 5 critical input variables. The findings suggest that these 5 variables are adequate for the precise classification and identification of "shipment status". As shown in Table 3, for the training data, the DT model's accuracy is 45.3. Figure 4 shows the variable importance of 8 key inputs obtained through DT model to predict and classify the shipment status.

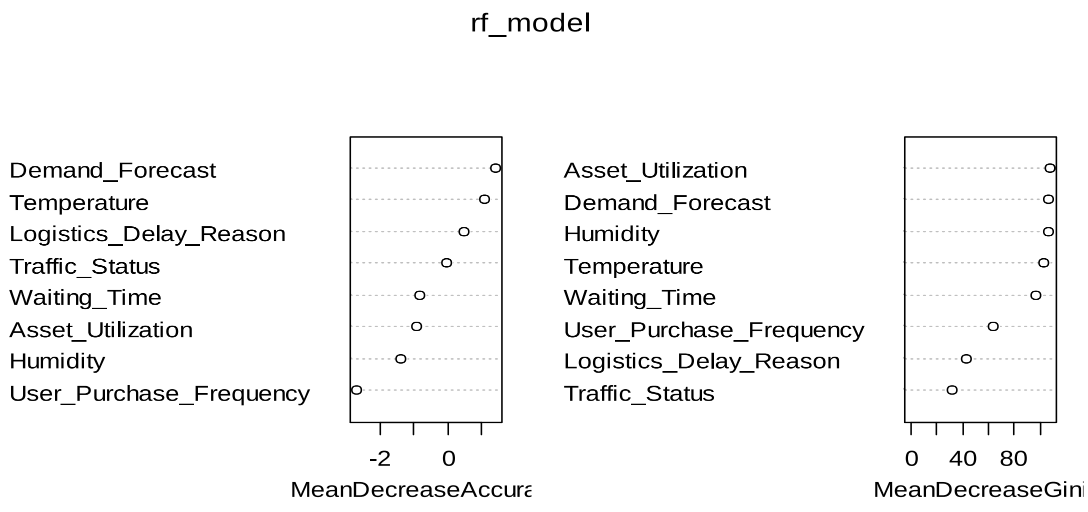

Figure 2 *Variable Importance Using Random Forest for Classification of "Shipment Status"*

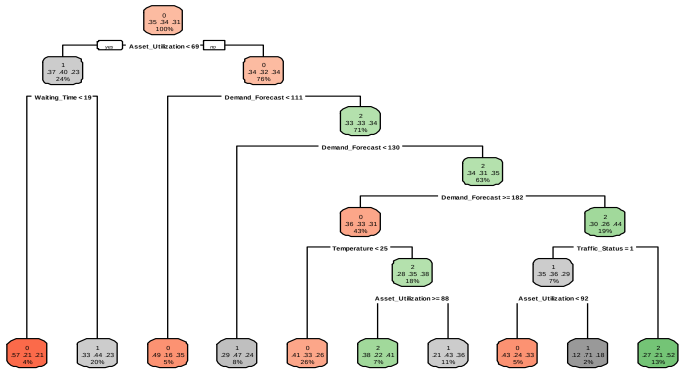

Figure 3*Decision Tree for Classification of "Shipment Status" in Logistics*

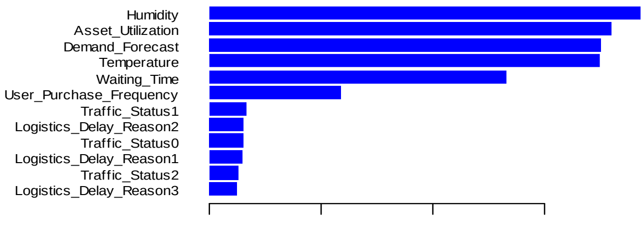

Figure 4 *Variable Importance Using Decision Tree for Classification of "Shipment Status"*

Experimental research indicates that the random forest and XGBoost exceeds all other AI-ML frameworks in terms of predictive efficacy. Moreover, its ability to produce feature importance metrics significantly improves interpretability, thereby providing critical clinical insights into indicators associated with "shipment status". The accuracy metrics for the RF and XGBoost models, as delineated in Table 3, are recorded as 100.0 and 100.0 percent or the total data as training dataset, signifying the highest accuracy rate among all models assessed. In contrast, the RF and XGBoost models demonstrated superior performance relative to other algorithms examined in the context of multiclass classification and the identification of "shipment status" in logistic systems. Figure 5 shows the model accuracy comparison using all the AI Models for multiclass classification of the "Shipment Status".

Table 3 *Summarization of the Accuracy for All AI-ML Models*

'Model'	'Neurons in Hidden Layers'	'Predictors'	'Output'	'Accuracy (%)'
Logistic Regression	--	8	3	39.9
Support Vector Machine	--	8	3	48.7
Artificial Neural Network	5	8	3	47.9
Random Forest	--	8	3	100.0
Decision Tree	--	8	3	45.3
XGBoost	--	8	3	100.0
K-NN	--	8	3	63.7

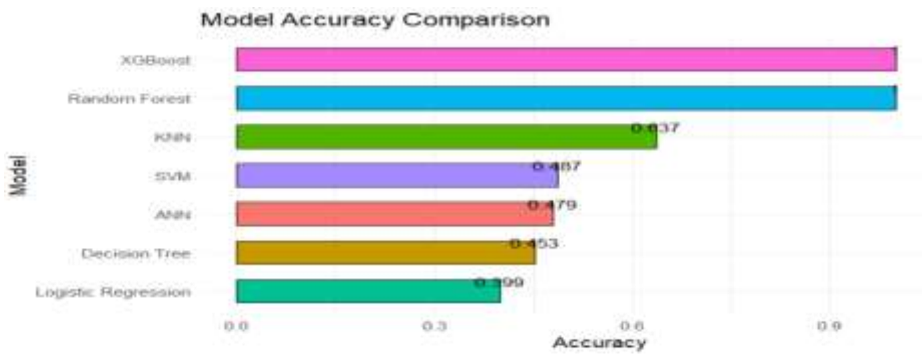

Figure 5 *Model Accuracy Comparison Using All the AI Models for Classification of "Shipment Status"*

6. Conclusion

The capability of AI-oriented intelligence to distinguish shipment statuses relies on multiple crucial aspects. A predominant factor is the selection of machine learning algorithms, with Extreme Gradient Boosting (XGBoost) exhibiting exceptional efficacy in predicting shipment statuses, attaining elevated accuracy levels in both training and testing datasets (Özdemir et al., 2024). The incorporation of AI technologies within logistics frameworks, including dynamic routing and real-time analytics, is also instrumental in augmenting the accuracy of shipment status classification by optimizing delivery pathways and refining demand forecasting (Badrinarayanan, 2024). Moreover, applying sophisticated deep learning frameworks, which skillfully understand complicated temporal dynamics, greatly boosts the effectiveness of recognizing delayed orders in convoluted supply chains (Bassiouni et al., 2024). The utilization of AI in predictive analytics and real-time data processing further bolsters precise shipment status classification by facilitating proactive decision-making and risk mitigation (Rane et al., 2024). The efficacy of the shipment classification is scrutinized through “Multinomial Logistic Regression”, “Support Vector Machine”, “Artificial Neural Network”, “Random Forest”, “Decision Tree”, “XGBoost”, and “K-Nearest Neighbour” models enabling training for multiclass classification and prediction model for shipment tracking. The performance of the DT model was appraised through the error rate, and the optimal tree was derived with 5 salient predictors, specifically "Asset Utilization", "Waiting Time", "Demand Forecast", "Temperature", and "Traffic Status" which collectively resulted in the minimum error. According to the experimental findings, the Random Forest and XGBoost models perform the best in terms of prediction accuracy than any conventional AI and ML model. With accuracy metrics of 100.00 and 100.00 for the whole training dataset, the RF and XGBoost models have the greatest accuracy of all the models that were tested.This study delineates the methodological framework for addressing multiclass classification, aiming to enhance logistic activities.

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