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Article

Intelligent Supply Chain Optimization in Emerging Markets Using Ensemble Machine Learning

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Abstract

In today's highly competitive and volatile environment, supply chains in emerging economies face ongoing challenges related to inventory management, demand forecasting, and distribution efficiency. This research proposes a predictive approach based on machine learning, specifically using ensemble stacking techniques, to optimize key logistics processes. Real-world data from a commercial company was used to develop a predictive framework that integrates various base algorithms Random Forest, CatBoost, XGBoost, Gradient Boosting, Decision Trees, and K-Nearest Neighbors combined through a Linear Regression meta-model. Performance evaluation using metrics such as MSE, RMSE, MAE, and R² revealed significant improvements in predictive accuracy compared to individual models, particularly in indicators such as material demand, purchase profitability, sales revenue, and inventory levels. The findings confirm that stacked models not only enhance forecasting capabilities but also offer a scalable, adaptable, and cost-effective solution to support logistics decision-making in resource-constrained contexts. This approach presents a strong alternative for boosting operational efficiency in supply chains across developing regions.

Keywords: supply chain; ensemble stacking; demand; inventory; distribution; machine learning

1. Introduction

In the current global context, supply chains face increasingly complex challenges, leading to economic damage [1]. Globalization has increased the interdependence between suppliers, distributors, and consumers, creating greater exposure to risks such as demand fluctuations [2], variability in delivery times, and inventory management difficulties [3]. These factors are exacerbated by uncertainty in demand and product performance, along with challenges in replenishment and decision-making under uncertain conditions, all of which are critical factors affecting the stability and efficiency of supply chains. These issues are particularly relevant in environments with higher risks associated with demand, distribution, and sales [4,5]. This situation requires companies to seek more advanced methods to optimize their logistics operations and improve decision-making accuracy in logistics strategies [6]. However, traditional logistics management cannot always anticipate these changes with sufficient accuracy, resulting in high costs, excess inventory, stockouts, and prolonged delivery times [7,8]. Therefore, predicting and managing these aspects efficiently has become a key challenge for companies [9,10].

To address these challenges, various methodologies based on advanced artificial intelligence and machine learning techniques have been explored in logistics management, as artificial intelligence stands out as a key tool for improving efficiency, sustainability, and agility in logistics [11,12]. As technology continues to advance, its integration into logistics operations promises to

transform further the way companies manage their supply chains and meet the growing demands of the global market [13–15]. Furthermore, machine learning is revolutionizing logistics management by improving operational efficiency and decision-making across various key areas [16–18]. By using advanced algorithms, ML enables the processing of large volumes of data to identify complex patterns and make accurate predictions, helping reduce costs, improve production, and optimize [18,19]. In particular, the use of predictive models, such as ensemble stacking, has shown great potential for improving prediction accuracy by combining multiple models to generate more robust results, as it is used to combine several predictive models, enhancing prediction accuracy and decision-making efficiency in various areas [20–22]. Thus, these approaches allow for considering various factors and complex patterns that influence supply chain logistics, from demand fluctuations to optimizing delivery times and inventory management.

Various studies have applied machine learning techniques to logistics management, such as [23], which developed a machine learning model to improve workforce planning in logistics, focusing on forecasting staffing needs based on the number of delivery points. This model was tested in a company and proved more accurate than manual forecasts and other automated models, especially in the short term. However, it suggests improvements for future research. The study [24] focused on improving product inventory management by proposing a deep reinforcement learning method that combines offline learning with online planning to optimize inventory levels. This approach outperforms traditional methods and is effective in supply chains with multiple products and stores. Furthermore, the research [25] proposed an approach to improve demand forecasting in the retail industry by predicting demand for each segment. A Bayesian model is then used to combine forecasts from different analytical techniques, which is validated with a case study, showing an improvement in the accuracy of daily demand predictions. Finally, the research [26] addressed inventory control to satisfy customer demand while minimizing costs by facing demand uncertainty. It used ensemble deep learning forecasting methods to predict future demand, optimizing inventory through safety stock calculation based on the forecasted demand distribution to maintain an adequate service level. However, these models often face limitations due to a lack of flexibility in the face of dynamic changes or the limited capacity of individual models to capture the full complexity of the system. Despite advancements in these approaches, many models do not meet expectations as they fail to adequately adapt to unpredictable market fluctuations or the interaction of multiple variables within the supply chain. This can result in inaccurate predictions that directly affect decision-making and the optimization of logistical resources.

For this reason, it was decided to investigate and optimize the supply chain of a commercial enterprise using machine learning models to improve accuracy, reduce costs, and optimize logistical processes in complex environments [27–29]. Therefore, this approach will enable better decision-making by integrating multiple information sources and forecasting variations in demand, delivery times, and inventories, allowing for more effective distribution.

It is worth noting that the significance of this research lies in its potential to transform logistics management, providing companies with more accurate and reliable tools to anticipate and manage resources efficiently, thereby improving efficiency and accuracy in logistics management across various sectors [30,31]. Additionally, improvements in logistics predictions not only optimize costs but also enhance customer satisfaction by ensuring a more agile and responsive supply chain.

2. Materials and Methods

The methodology used in this research is ensemble stacking, a machine-learning technique that improves prediction accuracy by combining the results of several models [32–34]. Instead of relying on a single algorithm, various models are employed to capture different patterns in the data. Each model makes its prediction, and a subsequent meta-model learns to merge them for better predictions optimally. Additionally, stacking is flexible and adapts to various types of data and problems, making it an effective tool in applications where high accuracy and reliability in predictions are required [35,36].

Thus, this approach improves logistical processes such as sourcing, inventory, and distribution. By integrating ensemble stacking, the supply chain's ability to adapt to market changes, better meet customer needs, and maintain operational efficiency at all times is optimized. Below, Figure 1 presents the diagram of the design of the intelligent supply chain model using ensemble stacking, which illustrates how this technique transforms the traditional supply chain into a more agile and precise one.

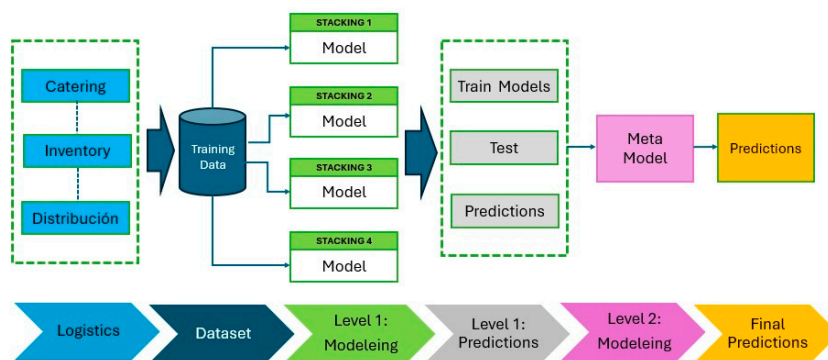


Figure 1. Diagram of the design of the intelligent supply chain model using the ensemble stacking technique.

Furthermore, this research addresses three fundamental areas within supply chain management: sourcing, inventory, and distribution. These areas are key to achieving effective prediction in logistics management. Specifically, it focuses on forecasting the material demand by location, the profitability of the material demand purchased by location, the monthly income generated from material sales by location, the total amount of material inventoried monthly by category, the average amount of material inventoried monthly by location, and the average amount of material distributed monthly by category.

2.1. Models used

The ensemble stacking model is built from the following base models, each selected for its characteristics and ability to capture specific patterns in the data:

- **Random Forest:** Builds multiple decision trees randomly and makes predictions by taking the consensus of these trees, which improves accuracy and reduces the risk of overfitting [37].
- **GBoost:** A boosting technique that enhances performance through the sequential creation of models, where each model corrects the errors of its predecessor, excelling in prediction tasks [38].
- **Gradient Boosting:** An iterative method where models are trained sequentially, each focusing on correcting the errors of the previous ones, and the final prediction is the weighted sum of all contributions [38].
- **CatBoost:** Based on decision trees, optimized for working with categorical data, providing fast and accurate performance on these datasets [38].
- **Decision Tree:** A model that divides the data into homogeneous subgroups through decisions based on specific features, easy to interpret and visually represent [39].
- **K-Nearest Neighbors (KNN):** A classification or regression method that predicts a value based on the "K" nearest data points to the instance in question, using a distance measure to determine proximity [40].
- **Regression Lineal (meta-model):** A technique that combines the predictions of several previous models, adjusting the results to improve overall accuracy by using the outputs of other models as the basis [40].

2.2. Phases of Ensemble Stacking

2.2.1. Data Preparation

The necessary data for training the model is collected and processed in this phase. The data is related to the following indicators: material demand forecasting by location, the profitability of material demand acquired by location, monthly income generated from material sales by location, the total amount of material inventoried monthly by category, the average amount of material inventoried monthly by location, and the average amount of material distributed monthly by category. Additionally, this phase includes data cleaning, normalization, converting categorical variables into numerical values, and splitting the data into training and testing sets. Figure 2 below shows the initial dataset of this project.

Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Producto	Cantidad	año	campo	almacen	ma de pre	dia	mes	Categoria	Costos	
0	0	0	0	0	0	0	0	0	EN BUSCA	18	2017	SEHS-CEN	SEHS	CEN	11	5	12	Grupo2	3
1	1	1	1	1	1	1	1	1	BIBLIA NR	52	2018	SEHS-CEN	SEHS	CEN	248	20	10	Grupo1	81
2	2	2	2	2	2	2	2	2	BIBLIA NR	9	2016	SEHS-CEN	SEHS	CEN	73	19	2	Grupo1	21
3	3	3	3	3	3	3	3	3	BIBLIA NR	14	2017	SEHS-CEN	SEHS	CEN	132	29	5	Grupo1	46
4	4	4	4	4	4	4	4	4	SOBRE CC	23	2017	SEHS-CEN	SEHS	CEN	265	13	12	Grupo4	68
5	5	5	5	5	5	5	5	5	BIBLIA NR	17	2017	SEHS-CEN	SEHS	CEN	91	21	5	Grupo1	28
6	6	6	6	6	6	6	6	6	GUJA DE I	21	2018	SEHS MPI	MPN	SUN	14	27	1	Grupo1	3
7	7	7	7	7	7	7	7	7	SOBRE CC	96	2017	SEHS APC	UPEU	LIBI	118	3	12	Grupo3	32
8	8	8	8	8	8	8	8	8	GUJA DE I	61	2018	SEHS ANC	ANOP	SUI	11	13	7	Grupo4	3
9	9	9	9	9	9	9	9	9	GUJA DE I	17	2018	SEHS MNI	MNO	SUR	153	30	7	Grupo1	36
10	10	10	10	10	10	10	10	10	REVISTA \	94	2017	SEHS MIC	MICOP	CC	446	12	6	Grupo1	127
11	11	11	11	11	11	11	11	11	GUJA DE I	5	2018	SEHS MIC	MICOP	SL	14	23	3	Grupo1	3
12	12	12	12	12	12	12	12	12	SOBRE CC	34	2017	SEHS APC	APCE	COL	183	16	2	Grupo1	56
13	13	13	13	13	13	13	13	13	SOBRE CC	1	2017	SEHS MIC	MICOP	LII	29	19	10	Grupo1	8
14	14	14	14	14	14	14	14	14	KIT ALUM	9	2017	SEHS MIC	MICOP	SL	115	5	2	Grupo1	30
15	15	15	15	15	15	15	15	15	VIVA CON	36	2018	SEHS MPI	MPN	COL	226	9	11	Grupo1	64
16	16	16	16	16	16	16	16	16	KIT ALUM	16	2017	SEHS MNI	MNO	SUR	192	27	12	Grupo3	60
17	17	17	17	17	17	17	17	17	SOBRE CC	25	2017	SEHS MPI	MPN	COL	3	28	1	Grupo1	3
18	18	18	18	18	18	18	18	18	KIT ALUM	139	2017	SEHS ANC	ANOP	SUI	29	24	6	Grupo4	9
19	19	19	19	19	19	19	19	19	VIVA CON	2	2017	SEHS ANC	ANOP	CO	179	12	7	Grupo4	58
20	20	20	20	20	20	20	20	20	VIVA CON	63	2016	SEHS MPI	MPN	COL	4	29	11	Grupo4	3
21	21	21	21	21	21	21	21	21	GUJA DE I	26	2018	SEHS ANC	CAIAM	SL	68	13	4	Grupo4	21

Figure 2. Project dataset.

2.2.2. Model Selection

In this phase, the machine learning algorithms that will be part of the ensemble stacking model are selected to choose a combination of base models that maximize prediction accuracy and improve system performance. Table 1 below shows each indicator with its selected base models and meta-model.

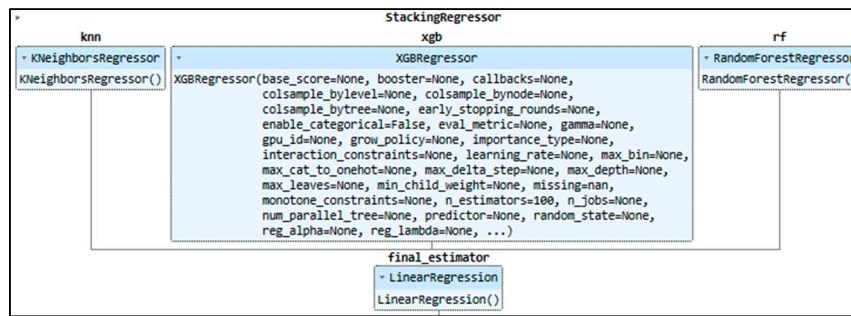
Table 1. Composition of Stacking Models.

Logistics Management	Indicator	Stacking	ML Models
Catering	Demand forecast for materials by location	1	K-Nearest Neighbors (KNN)
			XGBoost
			Random Forest
	Profitability of material purchased by location	2	Random Forest
			Decision Tree
			Gradient Boosting
	Monthly revenue generated by material sales by location	3	Linear Regression (meta-model)
			Gradient Boosting
			Catboost
Inventory	Total monthly inventory by category	1	Random Forest
			Linear Regression (meta-model)
			K-Nearest Neighbors (KNN)
			XGBoost

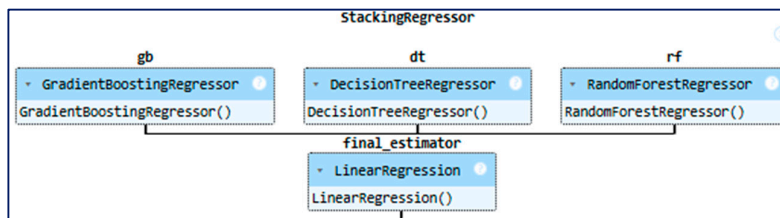
			Random Forest
			Linear Regression (meta-model)
	Average monthly inventory by location	2	Gradient Boosting
			CatBoost
			Random Forest
			Linear Regression (meta-model)
Distribution	Average monthly material distributed by category	1	Catboost
			K-Nearest Neighbors (KNN)
			XGBoost
			Linear Regression (meta-model)

2.2.3. Training of Base Model

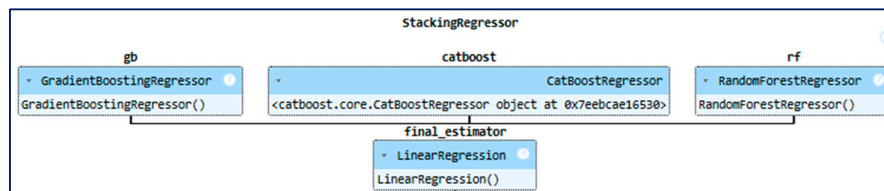
Each base model is trained independently using the training dataset. During this process, the hyperparameters of each model are adjusted to optimize their predictive capacity. Subsequently, the performance of each model is evaluated individually on the test set to ensure that each one is providing accurate predictions. In Figure 3, the training of the stacking model is shown for each indicator. For more details, see the following figure.



a)



b)



c)

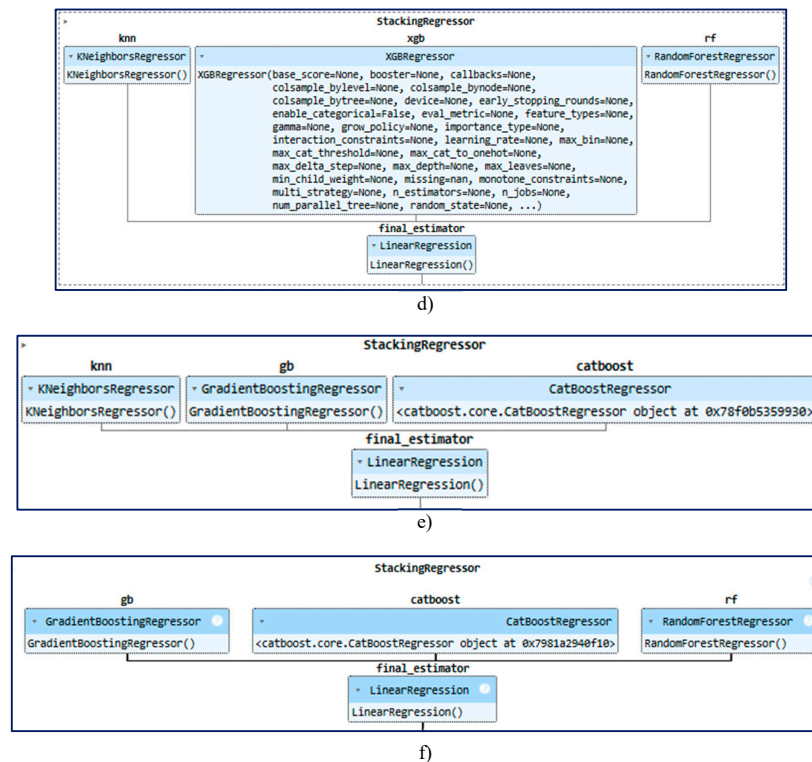


Figure 3. Model training. a) Indicator 1, b) Indicator 2, c) Indicator 3, d) Indicator 4, e) Indicator 5, f) Indicator 6.

2.2.4. Hyperparameter Optimization

In this stage, an optimization is carried out to find the best hyperparameters for each base model, maximizing its predictive capacity. This process is applied to all indicators considered in the study, such as demand forecasting, profitability, monthly revenue, inventory, and distribution. At the end of the process, the best hyperparameters for each base model are selected, and the obtained results are printed, improving the ensemble's accuracy and optimizing the stacking model's ability to make more precise predictions.

2.2.5. Formation of the Stack

In this phase, the Stacking model is constructed by incorporating both the optimized base models and the meta-model. The Stacking process facilitates the integration of predictions from the base models, enhancing the system's overall performance. During this phase, the predictions generated by the base models for each of the previously mentioned indicators are merged, resulting in a more robust model that maximizes the individual advantages of each base model. For more details, see Figure 4.

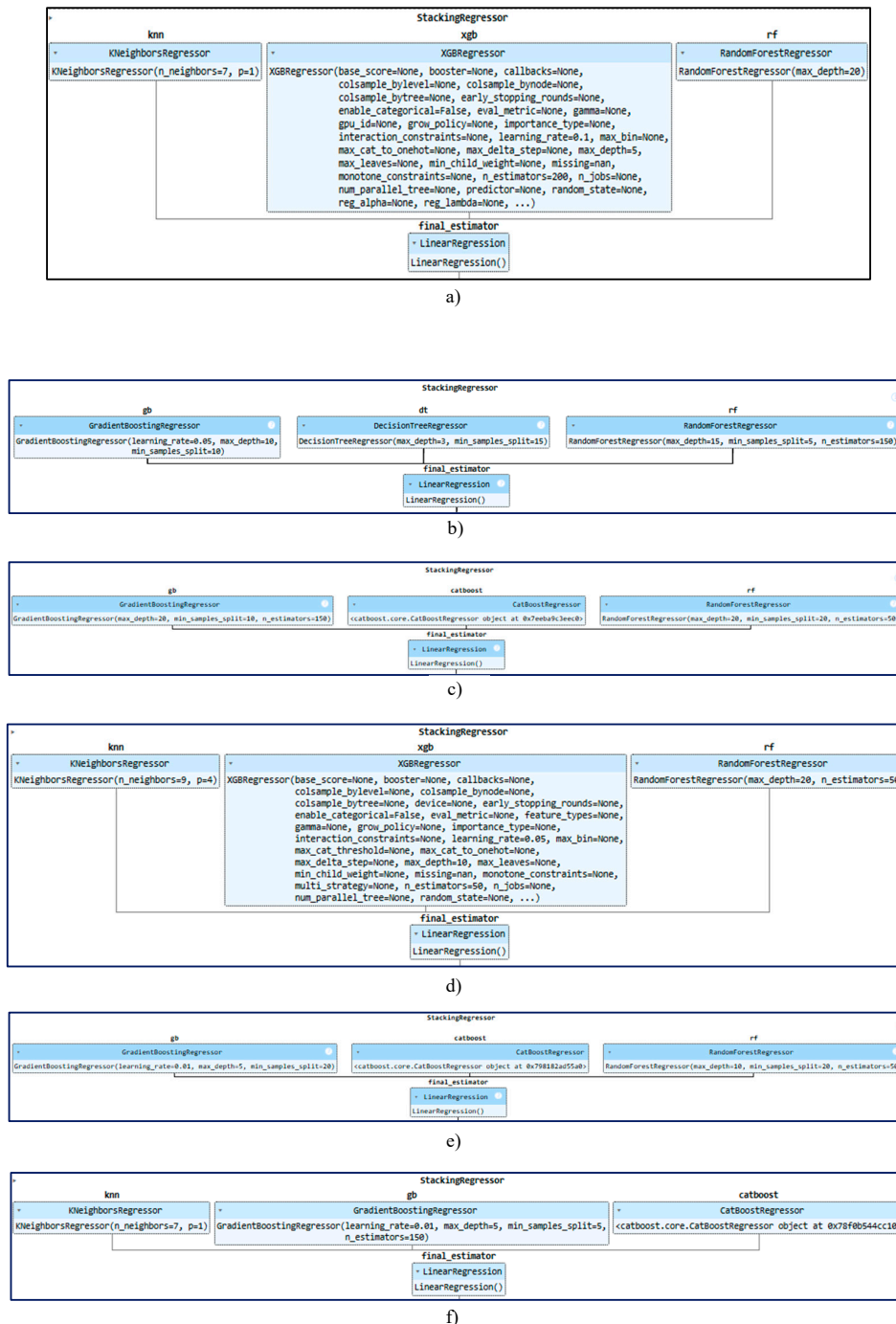


Figure 4. Formation of the stack. a) Indicator 1, b) Indicator 2, c) Indicator 3, d) Indicator 4, e) Indicator 5, f) Indicator 6.

2.2.6. Stack Prediction

The meta-model generates the final prediction by combining the outputs of the base models, improving the accuracy of the individual predictions from each model. In this phase, the final predictions for the six indicators are obtained: material demand, demand profitability, sales revenue, total inventory by category, average inventory by location, and material distributed by category. This process reflects the joint performance of the entire Stacking model, providing a more robust and accurate prediction for logistics management. The following code was used for each indicator.

```
[ ] # 6. STACK PREDICTION
y_pred = best_model.predict(x_test_scaled)
```

Figure 5. Stack Prediction.

2.2.7. Model Performance Metrics

Finally, the performance of the model is evaluated using metrics such as MSE (Mean Squared Error), R^2 (coefficient of determination), MAE (Mean Absolute Error), and RMSE (Root Mean Squared Error), which allow for assessing both the precision and the model's fit to the data. These metrics were chosen because they provide a comprehensive evaluation of performance in terms of absolute error and explanatory power of the model [41]. Therefore, this evaluation allows for verifying the model's effectiveness and making necessary adjustments. Below, the formulas for each metric to be used are presented.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

3. Results

This section presents the results obtained after implementing the ensemble stacking model for logistics management prediction. Various base algorithms were used, including Random Forest, XGBoost, Gradient Boosting, CatBoost, Decision Tree, and KNN. Subsequently, the performance of these models was combined through a meta-model based on linear regression, aiming to improve the overall model accuracy and reduce errors derived from individual models.

3.1. Model Performance

The model's performance was evaluated using several accuracy metrics, including MSE, R^2 , MAE, and RMSE, which allow for evaluating both the precision and the model's fit to the data. These metrics were chosen because they provide a comprehensive evaluation of performance in terms of absolute error and the model's explanatory power. Table 2 presents the results obtained from the prediction of material demand by location below. The prediction is also visualized in Figure 6.

Table 2. Evaluation of Metrics – Indicator 1.

Models	MSE	R^2	RMSE	MAE
KNN	0.0040	0.9068	0.0632	0.0482
XGBoost	0.0030	0.9295	0.0549	0.0420
Random Forest	0.0036	0.9149	0.0603	0.0458
Meta- model	0.0025	0.9419	0.0498	0.0379

Figure 6. Prediction of indicator 1.

In Table 3, the results obtained from the profitability of material demand purchased by location are presented, and the prediction is also visualized in Figure 7.

Table 3. Evaluation of Metrics – Indicator 2.

Models	MSE	R ²	RMSE	MAE
Gradient Boosting	0.0043	0.9010	0.0657	0.0485
Decision Tree	0.0092	0.7896	0.0958	0.0712
Random Forest	0.0046	0.8942	0.0680	0.0505
Meta-model	0.0039	0.9106	0.0625	0.0480

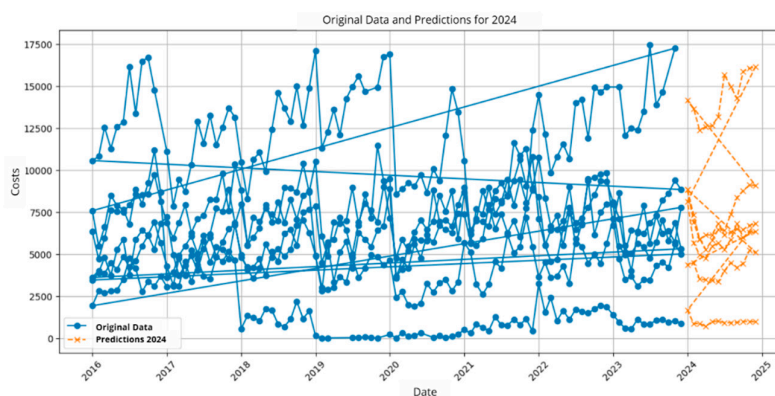


Figure 7. Prediction of Indicator 2.

In Table 4, the results obtained from monthly revenue generated by material sales by location are presented, and the prediction is also visualized in Figure 8.

Table 4. Evaluation of Metrics – Indicator 3.

Models	MSE	R ²	RMSE	MAE
Gradient Boosting	0.0043	0.9016	0.0653	0.0479
CatBoost	0.0042	0.9034	0.0648	0.0494
Random Forest	0.0044	0.8996	0.0660	0.0496
Meta-model	0.0038	0.9117	0.0619	0.0451

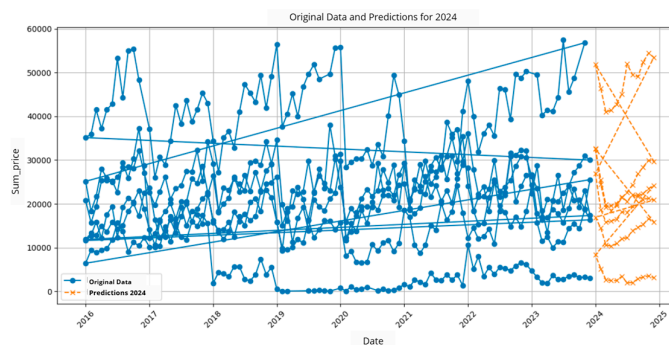
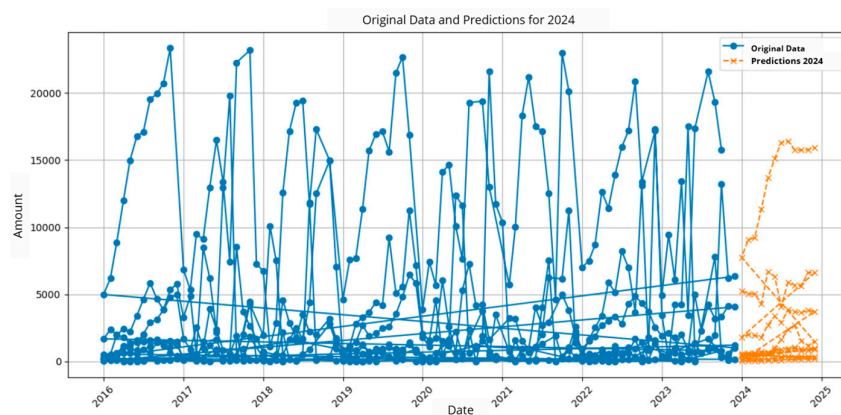


Figure 8. Prediction of Indicator 3.

In Table 5, the results obtained from the total amount of material inventoried monthly by category are presented, and the prediction is also visualized in Figure 9.

Table 5. Evaluation of Metrics – Indicator 4.

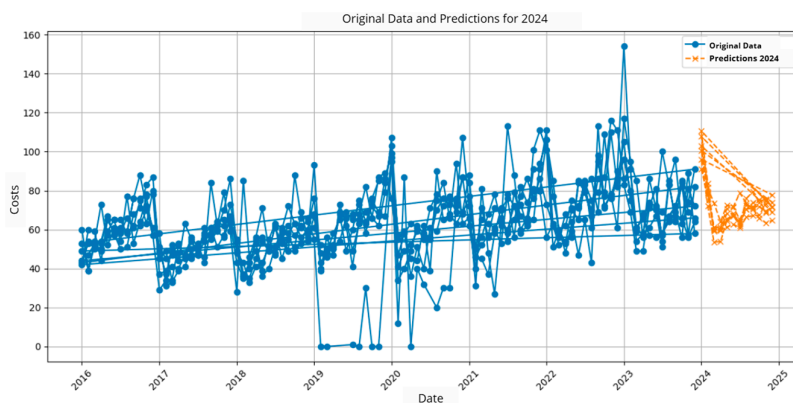
Models	MSE	R ²	RMSE	MAE
KNN	0.0194	0.7019	0.1392	0.0848
XGBoost	0.0315	0.5152	0.1775	0.1073
Random Forest	0.0240	0.6301	0.1551	0.0925
Meta-Model	0.0191	0.7058	0.0838	0.1383

**Figure 9.** Prediction of Indicator 4.

In Table 6, the results obtained from the average monthly inventory by location are presented, and the prediction is also visualized in Figure 10.

Table 6. Evaluation of Metrics – Indicator 5.

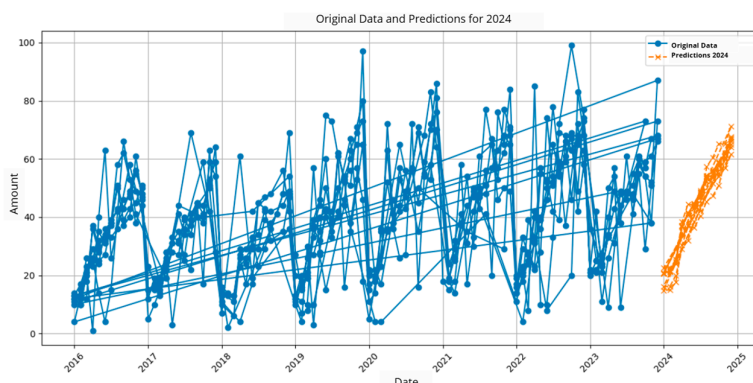
Models	MSE	R ²	RMSE	MAE
Gradient Boosting	0.0179	0.7064	0.1338	0.0828
CatBoost	0.0175	0.7124	0.1324	0.0850
Random Forest	0.0177	0.7097	0.1331	0.0852
Meta-Model	0.0147	0.7589	0.1213	0.0771

**Figure 10.** Prediction of Indicator 5.

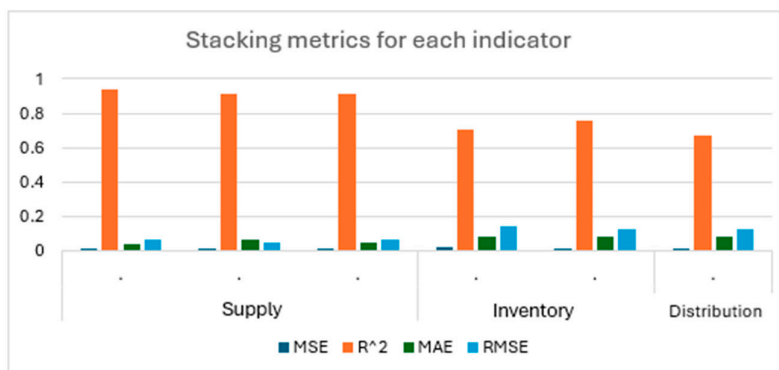
In Table 7, the results obtained from the average monthly material distributed by category are presented, and the prediction is also visualized in Figure 11.

Table 7. Evaluation of Metrics – Indicator 6.

Models	MSE	R ²	RMSE	MAE
KNN	0.0153	0.6588	0.1239	0.0865
XGBoost	0.0122	0.7299	0.1103	0.07726
CatBoost	0.0049	0.8910	0.0700	0.0520
Meta-Model	0.0147	0.6722	0.1214	0.0837

**Figure 11.** Prediction of Indicator 6.

As observed, the meta-model of the ensemble stacking shows significant improvement compared to the base models. The reduction in RMSE indicates higher precision in the predictions, while the increase in accuracy and F1-score metrics reflects more balanced performance, with fewer false positives and negatives. In Figure 12, the results by indicator are shown.

**Figure 12.** Stacking Metrics by Indicator.

4. Discussion

The results show that implementing an ensemble stacking model for logistics management prediction in intelligent supply chains significantly improves the accuracy of predictions. This result is consistent with previous studies such as research [23], which developed a machine learning model to forecast personnel needs in logistics, surpassing both manual and automatic methods. Likewise, research [24] optimizes inventory management using deep reinforcement learning, enhancing traditional methods. Additionally, research [25] combines analytical techniques with a Bayesian model to improve demand forecasting in the retail industry. Research [26] utilizes deep learning forecasts to optimize inventories. For more details on the results obtained, see Table 8.

Table 8. Comparison with Other Similar Studies.

Reference	Models	Metrics			
		MAE	RMSE	MSE	R2
[23]	MA	160.6	180.79	191979.06	-
	NS	163.43	184.08	191963.34	-
	LR	109.17	127.02	103381.32	-
	LGBM	76.02	82.96	42045.96	-
[24]	MA	0.666	1.001	-	0.24
	BNN	0.625	0.969	-	0.287
	MAML	0.636	0.956	-	0.306
[25]	LST	67.147	11.927	8.169	-
	Prophet	304.366	316.661	9.92	-
	Simple average	29.041	35.813	8.753	-
	BMA	27.393	32.887	8.177	-
[26]	MLP	5.05	5.93	12.64	-
	LSTM	4.18	5.21	10.12	-
	1D-CNN	6.2	7.96	14.76	-
	Proposed model	3.56	4.99	9.58	-

5. Conclusions

This study demonstrates that using an ensemble stacking model for logistics management prediction in intelligent supply chains substantially improves prediction accuracy compared to individual models. By combining several base algorithms, the ensemble model can capture complex patterns in the data and offer greater generalization capability across different logistics scenarios.

While the improved performance is a positive finding, it is important to consider the challenges associated with training time and the need for computational resources, which could be a limiting factor in certain environments. However, the results are highly promising and suggest that ensemble stacking-based approaches could be valuable for enhancing logistics management, particularly when accurate predictions are critical for strategic decision-making.

Future work is recommended to explore optimizing base models and applying advanced hyperparameter tuning techniques to reduce training time. It is also recommended that this model be implemented in real-time prediction scenarios, allowing for greater operational efficiency in the supply chain.

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