International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

CraftChain Logistics: A Complete Solution for Optimizing Various Operations

Roosewelt Antony[1], Onil Dsouza[2], John Gomez[3], Alec Lewis[4], Ankita Karia[5]

[1,2,3,4] UG Student, Department of Computer Engineering, St. Francis Institute of Technology, Mumbai
[5]Assistant Professor, Department of Computer Engineering, St. Francis Institute of Technology, Mumbai

Abstract
This paper presents "CraftChain Logistics" an integrated management system designed for Kondoth Fabrications, a metal fabrication company. The system aims to automate various tasks and eliminate the paper-based record-keeping system. CraftChain Logistics offers features for managing orders, employee salaries, and other essential business processes. The research paper discusses the system's design, implementation, and results, highlighting its potential benefits for enhancing operational efficiency and reducing administrative overhead. In an era marked by evolving consumer demands and heightened expectations for operational efficiency, businesses across various industries are continually seeking innovative solutions to remain competitive and sustain growth. The fabrication industry, known for its role in shaping the modern world, is no exception to this transformation. Recognizing the need to adapt and excel in this changing landscape, Kondoth Fabrications has embarked on a journey toward operational excellence with "CraftChain Logistics." CraftChain Logistics represents a comprehensive and integrated management system designed to empower Kondoth Fabrications with cutting-edge tools and capabilities. This system is engineered to address various facets of the business, from product management and order processing to resource optimization and data-driven insights. CraftChain Logistics is not just a management system; it is a strategic enabler, redefining how Kondoth Fabrications conducts its operations and engages with its customers.

Keywords: Logistics, Machine learning, Enterprise Resource Planning

1. Introduction

In the world of metal fabrication, where efficiency is key, Kondoth Fabrications is looking to modernize its operations. This paper presents "CraftChain Logistics," an automated system designed to streamline processes and reduce administrative workloads. CraftChain Logistics represents a significant step towards enhancing the efficiency and sustainability of metal fabrication businesses through automation, aiming to make Kondoth Fabrications more competitive in today's market.

CraftChain Logistics is a transformative platform aimed at optimizing resource allocation, streamlining workflows, employee management and boosting overall productivity. We are providing a system to the firm that ensures effective utilization of equipment, materials, and labor, resulting in cost savings. The system is designed to cater the specific needs of the business to improve their resource management practices. We understand the challenges faced by the enterprise in efficiently managing their resources and several other operations are developing a solution that simplifies and enhances this critical aspect of operations. The lack of inventory during big orders is one of the problems most of the businesses face today, so we are planning to use machine learning to overcome this by using Demand prediction, that would help in knowing the demand of commodities in the future.

2. Literature review

The authors of this paper [1] conduct an extensive literature survey to highlight the importance of efficient inventory management. They explored the application of machine learning, particularly the XGBoost algorithm, for demand forecasting to enhance inventory management. By training the XGBoost model using historical sales data, they predicted future product demand. The accuracy of demand predictions is assessed using Root Mean Square Error (RMSE) values. The study emphasizes the improvement in accuracy with the inclusion of more historical data. The survey discusses various inventory management aspects, highlighting the significance of inventory optimization, internal and external factors, and the role of AI and machine learning in enhancing inventory analysis, particularly in the e-commerce industry. The paper underscores the potential of the XGBoost algorithm in refining demand predictions and reducing inventory-related risks, benefiting small and medium businesses.

A software system that can significantly enhance how businesses manage their inventory was made clear by the authors of the paper [2]. This paper dealt with all the challenges associated with manual inventory management. The paper proposes a system to streamline all the processes and provide real-time sales and inventory tracking. Through automation, the system optimized inventory, enhanced accuracy, and improved efficiency. The overall scope included renewal lead time, stock valuation, quality management, and order forecasting.

Several inventory management challenges need to be addressed, which brought us to the paper [3], which addresses the usage of different inventory management techniques. ABC classification, economic order quantity (EOQ), VED, reorder level, safety stock, and inventory turnover ratio in inventory management are some of the techniques that were discussed in this paper. The study provides recommendations for improving inventory management and suggests the adoption of techniques like Just-In-Time inventory to enhance efficiency. ABC analysis helped in allocating managerial importance to various items in the inventory. Data analysis tasks were performed on several tasks. EOQ here was used to find the optimal order quantity for businesses to minimize logistics costs. Vital Essential and Desirable analysis was done mainly for control of spare parts keeping given the criticality to production. All of the techniques mentioned above contained their formulas.

Paper [4] follows a similar approach to paper [3] which involves using sales data for prediction. The authors of this paper focused on predicting business growth in the e-commerce sector using machine learning algorithms. Holt's Linear Trend Model from Time series analysis predicted values for future forecasting. It highlighted the limitation of traditional analysis methods for sales prediction prompting the adoption of machine learning as a powerful tool for identifying patterns and generating solutions. The author concluded sales forecasting is a boon for an ERP system as well as customer demands.

The importance of data in ML systems and the need for models to adapt to new input data continuously. was discussed in paper[5]. It highlights the challenges faced in traditional ML processes, such as the requirement for expertise in various mathematical concepts and programming languages. The introduction of AutoML aims to alleviate these challenges by automating processes like model selection and hyperparameter optimization.The results demonstrate that AutoML methods, particularly TPOT, offer advantages in terms of efficiency and accuracy compared to traditional ML approaches. Additionally, the study highlights the importance of selecting appropriate evaluation metrics beyond accuracy, such as precision and recall, for comprehensive model assessment. However, further exploration of evaluation metrics and improvements in AutoML tools are suggested for future work.

The study compares the performance of five regression techniques (Random Forest, Extreme Gradient Boosting, Gradient Boosting, Adaptive Boosting, and Artificial Neural Network) with a hybrid model (RF-XGBoost-LR) for sales forecasting in a US-based retail chain. Various metrics such as mean squared error (MSE), R2 score, and mean absolute error (MAE) are considered for evaluation. The hybrid model RF-XGBoost-LR outperformed other models in terms of forecasting accuracy, showcasing its potential for improving decision-making in sales forecasting for retail chains. Limitations of the proposed hybrid model include the need for large training datasets and challenges in decision integration, highlighting areas for improvement and further research. This extract provides insights into the effectiveness of machine learning techniques, particularly the hybrid model, in sales forecasting for retail chains, while also acknowledging areas for refinement and future exploration[6].

In this research paper, the author focuses on the importance of accurate demand prediction in the retail industry, particularly in the context of Bangladesh. They emphasize that effective demand forecasting can significantly impact inventory management, reduce costs, and enhance customer satisfaction. The author proposes to use machine learning techniques to forecast product demand, considering various factors such as time, month, occasion, location of the shop, and past records. The paper discusses the significance of minimizing inventory costs and optimizing supply chain operations through accurate demand forecasting. The author explores three popular algorithms - K-Nearest Neighbor, Gaussian Naive Bayes, and Decision Tree Classifier - for predicting customer demand. The paper aims to identify the most effective technique for forecasting demand by evaluating different features and methodologies, drawing on previous literature and performance analysis[7].

3. Proposed Solution

The CraftChain Logistics system is designed to provide Kondoth Fabrications with a combination of integrations aimed at increasing efficiency, business efficiency and eliminating traditional data processing. Key elements of the system include a user interface that provides a clean and intuitive user interface to enhance the customer experience of product automation technology and software to simplify, control and optimize the process of monitoring, tracking and recycling products to reduce manual work. Providing advanced analytics and forecasting algorithms, the platform helps accurately predict demand patterns and data analysis can identify key outcomes to guide improvement continuity and strategic decision-making; This helps businesses plan resource allocation and scheduling to adapt to changing needs.

In this project we are implementing a system to keep track of orders, product sold, salaries and several different operations. The historical data is used in the process of sales forecasting and demand forecasting. We are using several algorithms like Support Vector Machine (SVM), Autoregressive Integrated Moving Average (ARIMA), Random Forest (RF), AdaBoost, and XGBoost. The best performing algorithm is chosen for the future predictions. This involves comparing the performance of different algorithms using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R2 Score to ensure the chosen model provides the most reliable predictions. The system also calculates employee salaries based on various factors such as hours worked, overtime, bonuses, and deductions. By automating this process, this ensures accuracy and timeliness in payroll management, reducing errors and eliminating the need for manual calculations. By integrating these advanced algorithms into the system, CraftChain Logistics optimizes decision-making processes, minimizes risks, and enhances overall efficiency in supply chain management. Additionally, continuous monitoring and retraining of the models ensure that predictions remain accurate and up-to-date as data patterns evolve over time.

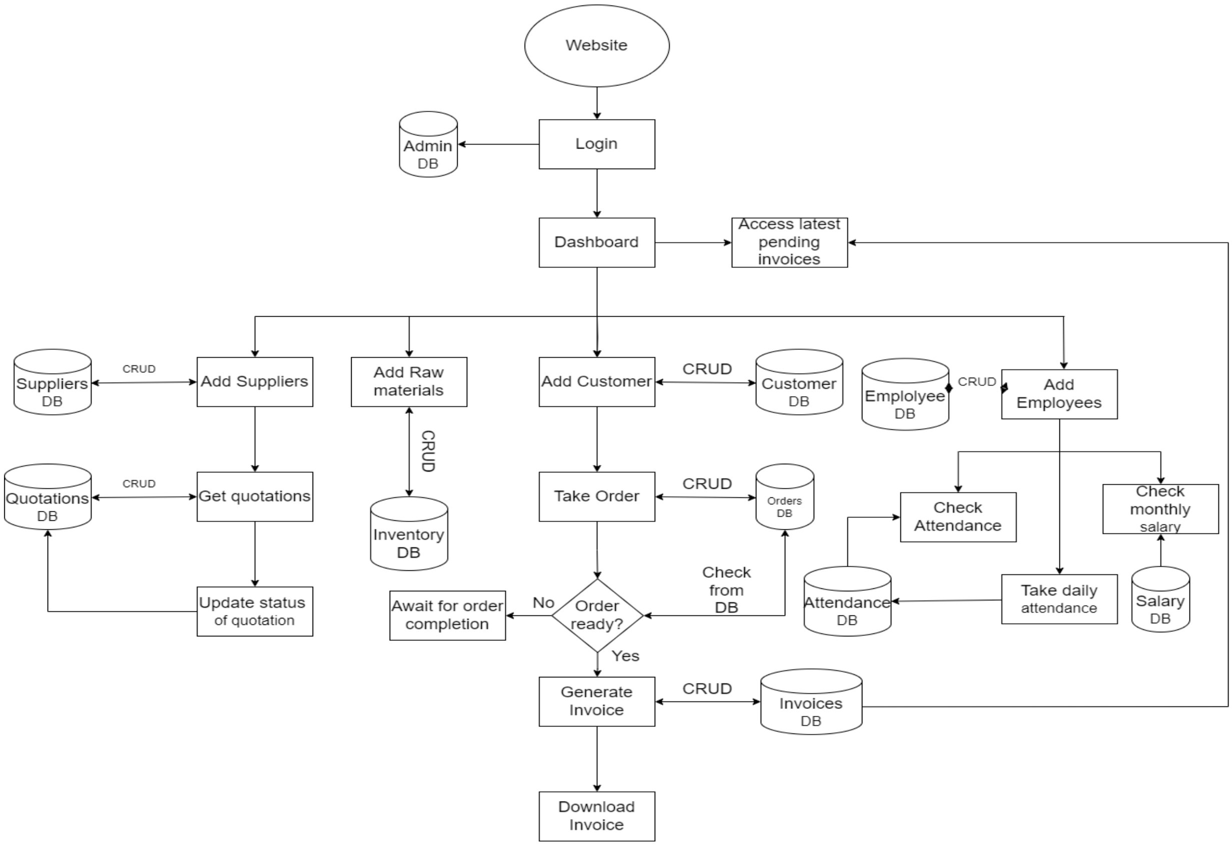


Fig. 1 Workflow of System

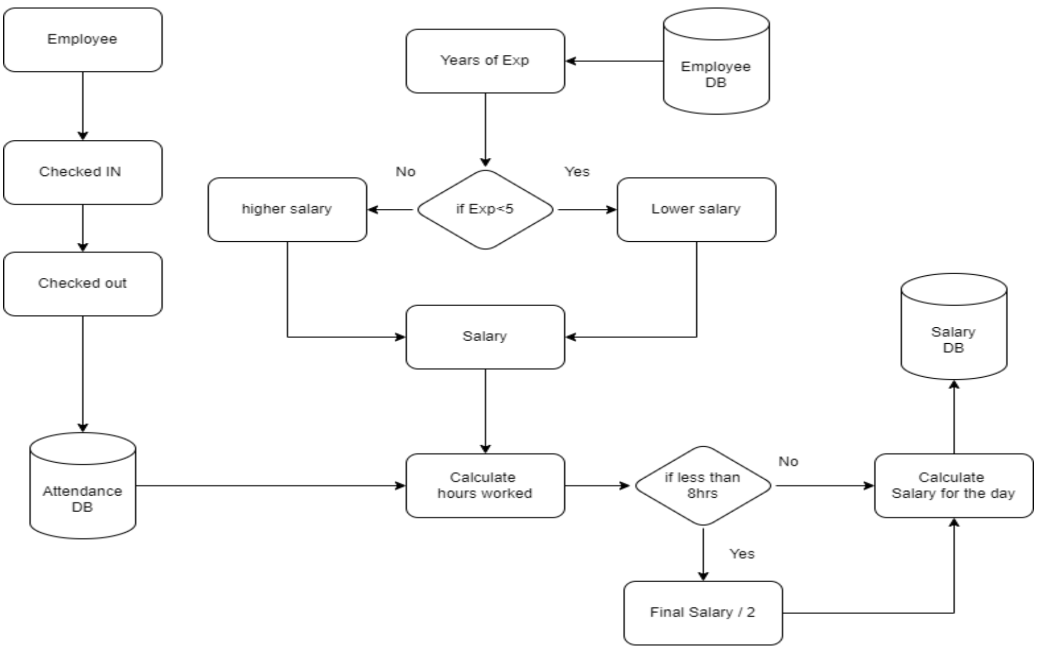


Fig. 2 Dynamic Salary Calculator

Support Vector Machine (SVM): Support Vector Machine is a type of supervised machine learning. Its main goal is to find the best line to separate different groups of data or predict outcomes. It helps understand challenges like demand differences and market unpredictability. SVM models provide real-time analysis, aiding on-time delivery, reducing inefficiencies, and minimizing revenue loss, boosting customer satisfaction.

Implementation:

1. Define features and responsible variables and initialize SVM Hyperparemater.
2. Divide data into train and test sets, preferably 70% and 30% respectively.
3. Use the SVM model on the training set.
4. Save the final model.
5. Make predictions using a test set.
6. Find performance metrics.
7. Validate the model.

In our project, we employ Support Vector Machine (SVM) for forecasting future sales trends. Initially, we engage in feature engineering to extract meaningful insights from the data, concentrating on variables such as monthly sales and sales dynamics over time. Subsequently, we train the SVM model, fine-tuning its parameters to grasp underlying patterns within the dataset. Lastly, we assess the model's efficacy using metrics like Mean Absolute Percentage Error (MAPE) to gauge its ability to accurately predict actual sales figures.

Extreme Gradient Boost (XGBoost): XGBoost is a Supervised Learning Algorithm that is used in Classification and Regression tasks. It builds on a series of decision trees, each correcting the errors of the previous one. It uses gradient descent to prevent overfitting and achieve high predictive accuracy. The final prediction is a weighted sum of the predictions from all the trees. We plan to use this model for demand forecasting. It is often known for its accuracy and speed, making it an ideal choice for demand forecasting tasks.

Model analysis: Here the initial tree takes an input of the entire dataset. It tries to make an initial prediction based on the original target values. The subsequent trees calculate the errors of the predictions. This process continues iteratively, with each new tree focusing on the mistakes made by the previous trees which results in a higher accuracy.

Hyperparameters of XGBoost:

- n estimators : It determines the number of trees needed to work on the problem.More number of trees may improve accuracy but would lead to higher training time.
- max depth : It sets an appropriate maximum depth to control the com- plexity of individual trees and prevents overfitting.
- min child weight : Adjust the minimum sum of instance weight needed to split a node, which is particularly relevant for imbalanced datasets.
- objective : It specifies the type of loss function to be used, eg. ’reg:squarederror’ can be used’ for regression and ’binary:logistic’ for binary classification.

Economic Order Quantity (EOQ): The Economic Order Quantity (EOQ) represents the optimal quantity a company should produce or purchase to strike a balance between holding and ordering costs, thereby reducing overall inventory expenses. This EOQ model takes into account factors such as demand rates, ordering expenses, and holding costs to determine the precise quantity that minimizes the combined costs of excessive inventory and frequent purchasing.

The EOQ formula is: EOQ = $\sqrt{2DS/H}$

In the EOQ formula:

- D stands for Demand rate of products(quantity sold)
- S represents the ordering cost incurred per purchase.
- H denotes the storage and holding cost associated with the products.

ARIMA (Autoregressive Integrated Moving Average): ARIMA is a method utilized in sales forecasting by analyzing historical sales data to detect patterns, seasonality, and fluctuations. It comprises three components: p, q, and d. The "autoregressive" component (p) examines how past values relate to the current one. The "integrated" component (d) ensures data stability over time. The "moving average" component (q) assesses the relationship between today's value and past errors.

Implementation involves:

1. Instantiating an ARIMA(p, d, q) model and fitting it to the monthly sales training set.
2. Projecting future time steps using the fitted model.
3. Calculating the MAPE (mean absolute percentage error) to evaluate accuracy.
4. Creating a line plot to visually compare actual and predicted sales, highlighting differences.

AdaBoost (Adaptive Boosting): AdaBoost is a machine learning method utilized for both classification and regression tasks. It amalgamates numerous weak learners, usually decision trees, to construct a robust classifier.

Here's a breakdown of its functioning:

1. Initialization: Begin by assigning equal weights to all training examples.
2. Iterative Training: Train a weak learner on the training data. Subsequently, amplify the weights of misclassified examples after each iteration. This process ensures subsequent weak learners focus more on challenging examples.
3. Weighted Voting: Assemble the weak learners into a strong classifier by assigning weights to each learner based on its performance.
4. Final Prediction: Predictions are made by considering the weighted combination of all weak learners.

This iterative procedure persists until a predefined number of weak learners are trained or until a perfect predictor is attained. AdaBoost proves highly effective when confronted with intricate datasets containing noise, often surpassing individual learners in performance.

Random Forest: The Random Forest algorithm stands out as a versatile and potent tool in machine learning, employed for both classification and regression tasks. Its functioning involves the creation of numerous decision trees during training, with the output being the mode (for classification) or mean (for regression) prediction of individual trees.

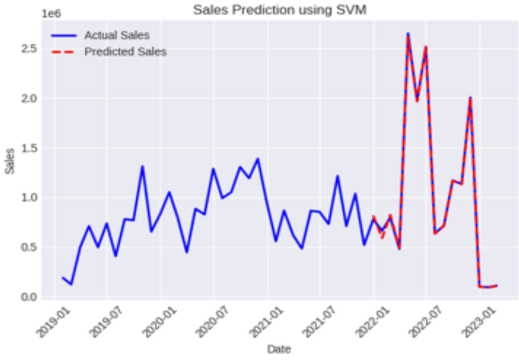
Here's a breakdown of its operation:

1. Bootstrapping: Randomly select subsets of the training data (with replacement) to train each decision tree.
2. Feature Randomness: At each node of the decision tree, only a random subset of features is considered for splitting. This technique, known as "feature bagging" or "feature subsampling," aids in decorrelating the trees and enhancing generalization.
3. Tree Building: Grow each decision tree to its maximum depth or until a stopping criterion is met. Techniques such as Gini impurity (for classification) or mean squared error (for regression) are commonly used to determine the best splits.

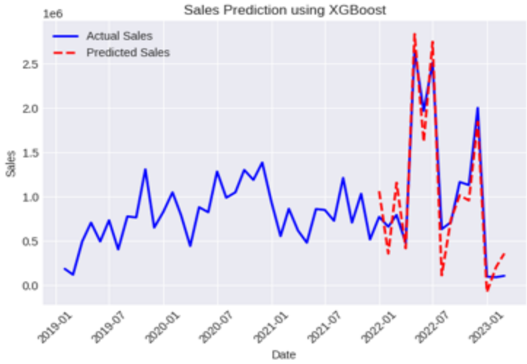
4. Voting or Averaging: In classification tasks, the mode of the predictions from all trees is considered as the final prediction. For regression tasks, the mean of the predictions is calculated.

4. Results and Discussion

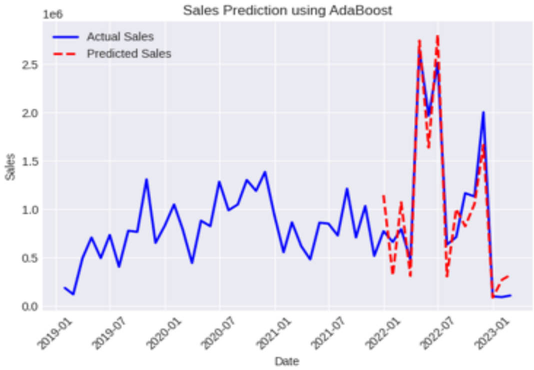
In this section, we present the results of our sales forecasting and demand forecasting experiments for different products using various algorithms. We used various algorithms for sales prediction which included Support Vector Machine (SVM), Autoregressive Integrated Moving Average (ARIMA), Random Forest (RF), AdaBoost, and XGBoost. The performance of each algorithm is evaluated based on multiple metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R2 Score.



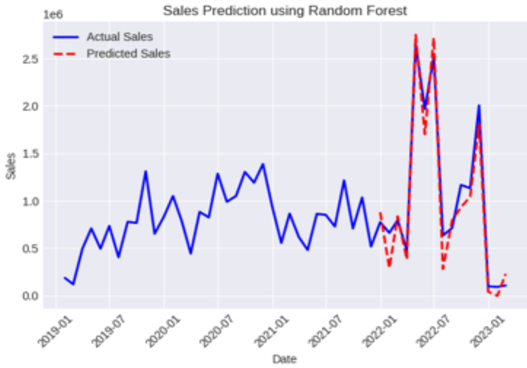
(a) SVM



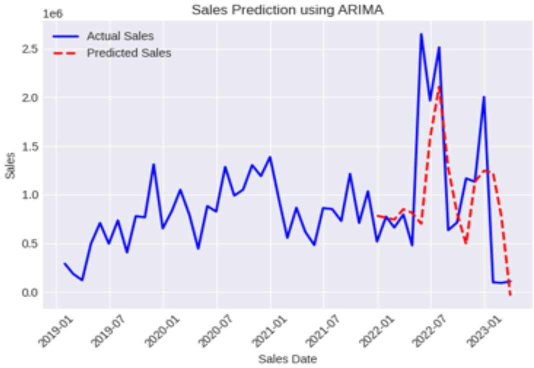
(b) XGBoost



(c) AdaBoost



(d) Random Forest



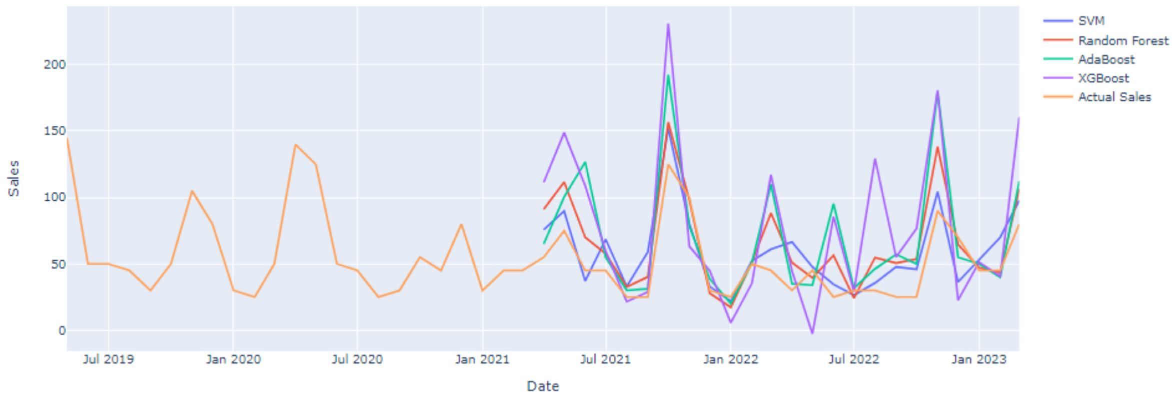
(e) ARIMA

Fig. 3 Performance of Sales Forecasting Algorithms

Model	MSE	MAE	R2 Score	MAPE
SVM	24843	14039	0.99	2.11
XGBoost	267760	244275	0.89	50.17
AdaBoost	255613	223933	0.91	55.6
Random Forest	190084	160732	0.95	33.23
ARIMA	20857161	314735	0.26	82.93

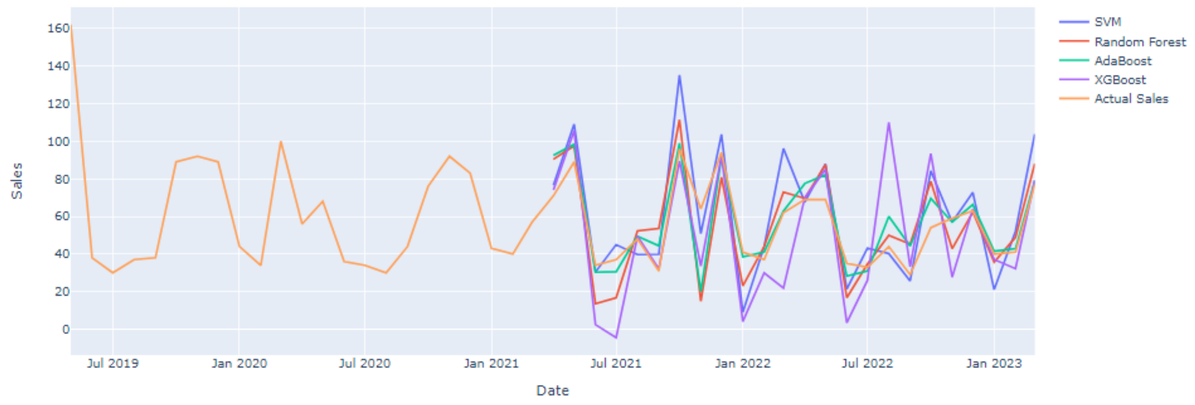
Table 1 Performance parameters of applied models

Based on the above results, we selected the Support Vector Machine (SVM) algorithm for our system because it demonstrated the lowest errors and the highest R2 score, indicating a strong fit to the data. SVM showed the lowest percentage error, suggesting its reliability in capturing the trends of the data. Random Forest also performed well with lower errors and a strong fit to the data, making it a viable alternative to SVM. While AdaBoost and XGBoost showed good performance, they had higher errors compared to SVM and Random Forest. ARIMA showed the poorest performance, indicating its limitations in capturing complex sales patterns.

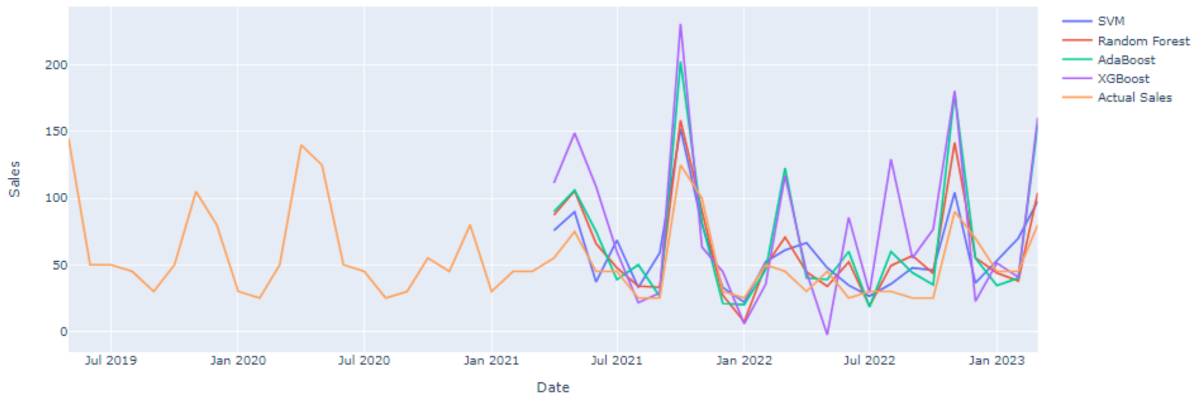


(a) MS Brackets

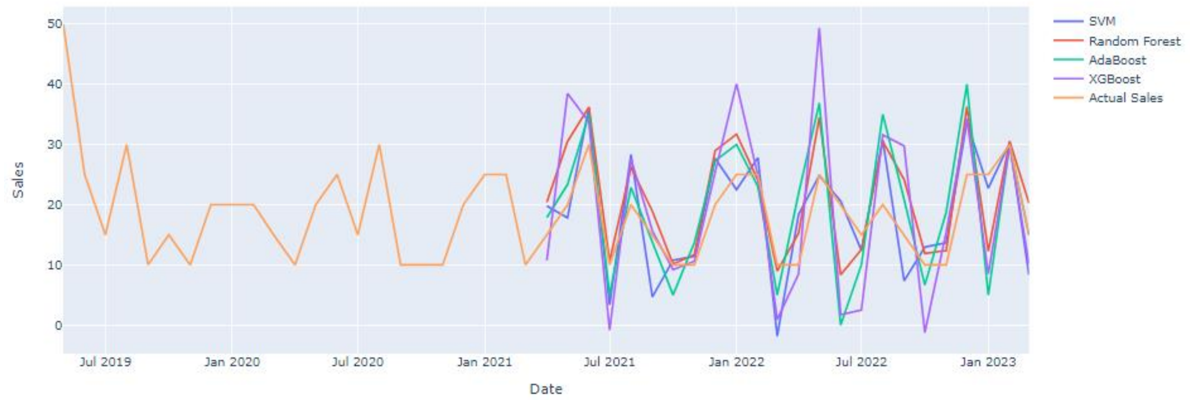
(b) Square Sheet Metal Junction Box



(c) Sheet Metal Boxes



(d) Junction Box (S)



(e) MS Platform

We used several algorithms, including Support Vector Machines (SVM), Random Forest (RF), AdaBoost (ADA), and XGBoost, for demand forecasting on various products. Each model was trained and evaluated to predict the sales of products such as MS Brackets, Square Sheet Metal Junction Box, Sheet Metal Boxes, Junction Box (S), and MS Platform. The plot above showcases the predictions made by each model alongside the actual sales data. By comparing these predictions, we can assess the performance of each algorithm in capturing the underlying patterns in the sales data and making accurate forecasts. Since different products exhibited different patterns of trends in their datasets, each model behaved differently when applied to the forecasting task. The unique characteristics of each product's sales data influenced how well each algorithm performed. Therefore, to determine the most suitable model for overall deployment, we took the average of all the evaluation metrics across all products

Model	MSE	RMSE	MAE	R2 Score
SVM	232.96	13.42	10.82	0.51
Random Forest	726.92	21.36	18.04	0.06
AdaBoost	1258.19	27.10	21.15	-0.41
XGBoost	1421.14	32.94	26.73	-1.32

Table 2 Comparison of Evaluation metrics(Average) for Different Products Using different models

SVM outperformed other models with the lowest MSE, RMSE, MAE, and the highest R2 Score, indicating superior accuracy and goodness of fit to the data. The positive R2 Score for SVM indicates that it explains a significant portion of the variance in the sales data, suggesting that it provides reliable predictions. Random Forest follows with slightly worse performance, while AdaBoost and XGBoost show even poorer results, with higher errors and negative R2 Scores, indicating poor predictive power and fit to the data. Overall, SVM demonstrates its suitability for demand forecasting due to its robust performance across different product types and data patterns. This was the model that was used in the system.

5. Conclusion

In conclusion, CraftChain Logistics is a web application for the fabrication business motivated by the need to enhance operational efficiency, reduce costs, improve supply chain visibility, and ultimately offer a competitive edge in the industry. By providing tools for streamlined logistics management, inventory control, order tracking, and data-driven decision-making, CraftChain Logistics aims to optimize the entire logistics process. It not only benefits businesses in terms of productivity and profitability but also contributes to customer satisfaction and a more sustainable approach to operations. With its scalability and focus on risk mitigation, this platform offers a comprehensive solution to address the complex logistics challenges faced by fabrication businesses in the modern world.

6. Acknowledgement

We would like to express our gratitude to all the authors whose research papers and contributions formed the foundation of our project. It not only provided us with essential insights but also inspired us to explore new avenues in our research. We also extend our heartfelt appreciation to the faculty of our college for their unwavering support and encouragement throughout this project. Their guidance
and expertise were instrumental in shaping our ideas and methodology.

7. References

1. Javaregowda, Madhuri B, Praveen Kumar, Pradyumna J, Prateek G, Pragathi. ”Inventory management using Machine Learning.International Journal of Engineering and Technical Research”. 9, 2020.

2. Punam Khobragade, Roshni Selokar, Rina Maraskolhe, Prof.ManjushaTalmale, (2018). ”Research paper on Inventory management system”.-ISSN: 2395-0056, 2018.
3. Sheakh, Tariq. A Study of ”Inventory Management SystemCase Study. Journal of Dynamical and Control Systems”. 10. 1176-1190, 2018.
4. S. Kulshrestha and M. L. Saini, ”Study for the Prediction of E-Commerce Business Market Growth using Machine Learning Algorithm,” 5th IEEE International Conference on RecentAdvances and Innovations in Engineering (ICRAIE), Jaipur, India, 2020, pp. 1-6, 2020.
5. Kavikondala, Akanksha and Muppalla, Vivek and Prakasha, Dr. Krishna and Acharya, Vasundhara. ”Automated Retraining of Machine Learning Models”. 8.445-452.10.35940/ijitee.L3322.1081219, 2019.
6. Mitra, A., Jain, A., Kishore, A. et al. A Comparative Study of Demand Forecasting Models for a Multi-Channel Retail Company: A Novel Hybrid Machine Learning Approach. Oper. Res. Forum 3, 58 . https://doi.org/10.1007/s43069-022-00166-4, 2020.
7. M. A. I. Arif, S. I. Sany, F. I. Nahin and A. S. A. Rabby, "Comparison Study: Product Demand Forecasting with Machine Learning for Shop," 8th International Conference System Modeling and Advancement in Research Trends (SMART), Moradabad, India, 2019, pp. 171-176, doi: 10.1109/SMART46866.2019.9117395. 2019.