

Enhancing Marketing Performance Of Coconut Farmers Through AI-Enabled Supply Chain Optimization

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Abstract

Coconut farming is an important sector of rural livelihoods and agri-based economies, though inefficiencies within conventional supply chain systems tend to curtail the marketing performance of farmers, their income stability, and access to the market. This paper explores how the use of artificial intelligence (AI)-based supply chain optimization can be used to boost the marketing performance of coconut farmers. The study investigates how AI-based applications, including demand forecasting, price prediction, inventory optimization, and logistics planning, can be used to deal with the issues associated with price fluctuations, losses after harvesting, and information asymmetry. The proposed research CocoSMART-ML is examined within the framework of mixed-method research, the primary data were gathered with the help of coconut farmers, the middlemen and the marketing agencies, and the secondary data served as the supportive tool of revealing the main flaws of the supply chain. The machine learning models were used to study the demand patterns, optimize the distribution routes, and predict the prices of markets. Indicators that were used to measure the performance of marketing were market reach, growth in sales, price realization, and profitability of the farmers. The results indicate that optimization of the supply chain with AI can affect the efficiency of decisions, decrease operational expenses, and increase the level of transparency throughout the coconut value chain. The farmers who embraced the use of AI in farming practices reported better market access, enhancement in price realization, and less reliance on intermediaries. Moreover, the implementation of AI can help in sustainable supply chain management through the reduction of wastage and enhancing the use of resources. The paper identifies the opportunities of revolutionizing agricultural supply chains and enhancing marketing performance of small and marginal coconut farmers enabled by AI technologies. The findings give useful information to policy-makers, agri-tech developers, and cooperatives to encourage the use of AI as a strategic instrument to improve marketing performance and guarantee long-term sustainability in the coconut farming industry.

Keywords- Artificial Intelligence, Supply Chain Optimization, Marketing Performance, Coconut Farming, Agricultural Supply Chains.

1. Introduction

Coconut agriculture is a key source of income to millions of small and marginal farmers in the tropical areas as well as agri-based economies [1]. Even though the coconut industry is economically significant, the industry has remained vulnerable to the irrelevance of ineffective supply chain management, fluctuating prices, excessive post-harvest losses, and market inaccessibility. Conventional supply chains are mostly manual, disjointed, and reliant on intermediaries and this usually translates to low price realisations and poor marketing by farmers. All these inefficiencies make it clear that there is an urgent necessity to find smart, data-based solutions that will help to optimize the coordination of supply chains and lead to better marketing performance [2]. The recent developments in artificial intelligence (AI) and machine learning (ML) have shown that optimization of agricultural supply chains has a significant potential in terms of accurate predictions, intelligent decision-making, and real-time optimization. Nevertheless, AI application in smallholder agricultural systems is not widely used

because most sophisticated models are complex, expensive, and incomprehensible [3]. Current research tends to present single elements of price prediction or demand forecasting, whereas the necessity of integrated, farmer-centric model that is aimed to cover the whole supply chain since the harvest planning to the market delivery is ignored. To fill these gaps, this paper suggests an AI-based supply chain optimization framework that is specific to coconut farmers with the focus on simplicity, interpretability, and practical applicability [4]. The suggested solution combines several steps, such as the reliability-weighted fusion of data, the imputation of data based on seasonal similarity, the forecasting of demand and price with quantile-based ensemble models, the optimization of the logistics with the help of ML, the impartiality-conscious matching between the farmers and the buyers, and decision support through data. In contrast to the sophisticated deep learning frameworks, the suggested approaches are based on simple, but original extensions of traditional machine learning algorithms, which makes them applicable in the real world implementation in the resources-limited field of agriculture.

Moreover, the paper assesses how AI-based optimization of the supply chain can enhance the essential marketing performance metrics of price realisation, market access, sales increase and profitability. The research offers a high-quality empirical data regarding the usefulness of AI adoption in marketing performance improvement by including causal and uplift-based evaluation methods [5]. The results should provide useful information to policymakers, farmer cooperatives and agri-tech developers who have scalable and sustainable AI solutions to enhance coconut supply chains.

2. Literature survey

In [6], Anjanadevi, B et al., introduced an IoT-based supply chain monitoring system implemented to achieve RFID technology and machine learning to enhance logistics transparency and security. The suggested system used XGBoost algorithm to estimate the important attributes of sold products, such as delays in delivery and possible cases of fraud. The products in the supply chain were tracked using RFID based authentication and to check the legitimacy of the items. A single product tag was experimentally validated in a setting of an IoT environment, which allowed gathering authentication and data concerning delivery. Moreover, the research determined the root factors of delivery delays and that adding the framework with product tagging, based on demands, would allow storing all the data and influencing more efficient decision-making in supply chain activities.

In [7], Santoso, I et al., (2021) performed a systematic review of machine learning applications in the agri-food supply chain, and they emphasized that machine learning algorithms could help to enhance proactive and data-driven decision-making by providing real-time analytical insights in the supply chain. It highlighted the role of the ML techniques in enhancing better management practices, productivity, and sustainability in agri-food supply chains, and advised researchers, practitioners, and policymakers on the proper adoption of ML.

In [8], Sadaphal, S et al., (2021) suggested a Direct Farm-to-Consumer (DFC) application, which is an agri-hub smart to enable the purchase and sale of agricultural products. The system combined the mobile computing, cloud computing and machine learning to balance between demand and sales. Support Vector Machine (SVM) algorithm has been used based on a custom training dataset to increase accuracy of prediction and efficiency in decision making in the DFC framework.

In [9], Judijanto L et al., (2024) analyzed the effects of machine learning algorithms, demand forecasts and automation mechanisms on responsive inventory control in the retail segment of the Central Java with a quantitative design. The results of the analysis

based on data on 160 respondents depicted that the automation systems and demand prediction had a strong positive impact on the inventory responsiveness, whereas machine learning algorithms demonstrate a strong yet negative correlation. The findings indicate how automation can be used to ensure efficient use of the processes and how precise prediction of demand is necessary in matching inventory with the market demands.

In [10], Kumari, S et al used bibliometric and visualization tools to identify research trends in artificial intelligence and machine learning application in agricultural supply chain. It can be stated that the results show a strong increase in the number of publications, which represents the rising popularity of AI- and ML-based solutions. The study conducted geographic mapping, keyword and network analysis, citation and factor analysis, which identified a transition of agricultural supply chains by using precision agriculture, deep learning, reinforcement learning, food safety, and intelligent food supply chain. Besides, the research was a roadmap to future research because it determined essential research clusters and research emergent themes, thus outlining the possible paths of machine learning application in agricultural supply chains.

In [11], Benitez-Garcia, I et al., (2025) formulated mathematical and dynamic agri-food tomato supply chain models with a compartmental modeling framework and studied the system behavior in terms of stability and dynamic models. The sustainability index involved to measure the environmental impact of the supply chain included the waste diversion rate, which allowed quantifying the sustainability performance. Also, sensitivity analysis to confirm the strength of the proposed models was done to support the findings of the study.

In [12], Islam et al., (2025) examined the primary uses of artificial intelligence, machine learning, and deep Learning in marketing, supply chain management, financial analytics, and human resource management and found that they were useful in solving complex business problems. Other emerging trends that were discussed during the review include explainable AI, the combination of AI and IoT and blockchain, and AI-based sustainability efforts. Although these improvements were made, issues associated with algorithmic bias, quality of data, high cost of implementation, and weak regulations were observed. The paper also identified research gaps, specifically the inexistence of empirical research on the use of AI in small and medium enterprises and developing economies, and gave the future research and practice recommendations.

3. Proposed method

The suggested system (called CocoSMART-ML) creates a decision-support pipeline based on farm-market data, which translates the data into actionable recommendations: what, when, where, how, and how to sell [13]. It is a method that is meant to be easy, deployable and interpretable by lightweight ML models.

3.1 Data collection

The proposed AI-enabled supply chain optimization framework will base itself on the data collection and integration stage. Coconuts supply chains have multi-stakeholders and heterogeneous information, such as farmers, markets, logistics suppliers, and storage facilities. Such data sources tend to be fragmented, inconsistent and incomplete because of manual record-keeping, limited digital infrastructure and uncertainty of the environment [14]. Thus, it is critical to have a good data integration system to provide high-quality input to bottom machine learning models and decision-support systems.

Data sources

- The proposed system gathers multi-dimensional information in the following sources:
- Data at the farm level: harvest quantity, harvest date, coconut grade, the farm location and the historical yield data.
- Market data: daily mandi price, wholesale and retail price, volume of demand and buyer orders.
- Weather conditions: rainfall, temperature, humidity and extreme weather conditions that influence transportation and yield.
- Logistics information: the distance of transport, the approximate time it will take, the situation of the road, and the delays during delivery.
- Storage information: warehouse capacity, storage time, cost of storage and spoilage rates.
- Energy and cost information: information on the cost of fuel and the cost of handling in relation to transportation decisions.
- To integrate different data sources that are used in the marketing of coconuts, weighted Source Reliability Ensemble (WSRE) is applied during the data collection and integration phase [15]. There is a tendency of agricultural data being noisy, incomplete and inconsistent, increasing the risk of carrying over errors to machine learning models at the downstream. WSRE addresses this problem by estimating the trustworthiness of each source of data and assigning it weight in accordance.

i. Identification of data source

Let the set of data sources be:

$$S = \{s_1, s_2, \dots, s_n\} \quad (1)$$

In which the source s is the records of farmers harvests, mandi price, buyer demand, weather, logistics, storage, or fuel cost. Both sources give a feature X_s belonging to a given decision period.

ii. Reliability estimation for each source

Reliability score r_s is calculated using 3 measurable criteria in case of each data source s .

i. Missing data ratio

Data missing ration is estimated on the basis of each collection of data source. Higher missing ratios mean low reliability.

$$MR_s = \frac{\text{No of missing values in } X_s}{\text{Total number of observations}} \quad (2)$$

ii. Variance Stability

$$VS_s = \frac{1}{1 + \sigma_s^2} \quad (3)$$

Where σ_s^2 denotes the source data variance. Data that is less variable (more stable) are said to be more reliable.

iii. Historical agreement

This provides consistency between the source data and a point of reference (e.g., regional averages of prices or shop survey records).

$$HA_s = \text{corr}(X_s, X_{ref}) \quad (4)$$

3.2 Data cleaning and Handling missing values

Manual data entry, network problems or delayed reporting tend to leave agricultural supply chain information incomplete or missing, which includes coconut prices, demand, yield, and transport delays. The traditional imputation procedures (mean, median, linear interpolation) do not take into account seasonality and climatic effects that are vital in agriculture [16]. This limitation is overcome by Seasonal Similarity Imputation (SSI) which uses repeating similarity of seasons and similarity of weather.

The assumption made by SSI is that the behavior of agricultural variables within a week with a specific seasonal and climatic pattern is similar in nature to the behavior of a week of the same pattern. Hence, the missing values are approximated based on the data of the past weeks which are similar to the current week instead of the global averages.

Identification of missing values

Where X_t is a time-series variable (price, demand, or yield), at time. In case X_t is missing, SSI fills the gap with the help of past data. The identification of the missing values is carried out with the help of the following steps [17].

Step 1: Seasonal filtering

Determine previous year candidate weeks χ whereby

$$Season(t) = Season(t_i) \quad t_i \in \chi \quad (5)$$

Step 2: Climatic similarity

Calculate climatic distance R and T of each candidate week t_i .

$$d(t, t_i) = \sqrt{(R_t - R_{ti})^2 + (T_t - T_{ti})^2} \quad (6)$$

Lower distance $\rightarrow$ higher similarity.

Step 3: Select nearest seasonal neighbors

Select the k best weeks having distance minimum.

$$N_k(t) = \{t_1, t_2, \dots, t_k\} \quad (7)$$

Step 4: Weight computation

The neighbors are allocated weights of an inversional relation to their distance:

$$w_i = \frac{1}{d(t, t_i) + \epsilon} \quad (8)$$

where ϵ is a small constant in order to not divide by 0.

Normalize the weights

$$w'_i = \frac{w_i}{\sum_{j=1}^k w_j} \quad (9)$$

Step 5: Missing value imputation

X'_t is forecasted as a weighted average of the past values.

$$X'_t = \sum_{i=1}^k w'_i X_{ti} \quad (10)$$

3.3 Quality Grading

Price realization and preference by the buyer are heavily dependent on quality grading and readiness to harvest in the coconut marketing. In his chapter a novel TRML ML-based grading method is suggested to analyse the coconut grading [18].

TRML is solving this problem by incorporating human readable agricultural regulations and machine learning where transparency and accuracy are guaranteed. This hybrid design consumes less complexity of models but enhances trust and performance. TRML has two stages of operation:

Stage 1 – Rule-based filtering

Simple method of categorising coconuts based on expert-established categories of clearly immature or mature coconuts.

Where each sample of coconuts is given off as:

$$x = [w, d, a, c] \quad (11)$$

Where,

w is weight, kg, d diameter (cm), a age since flowering, months and c shell color index (not compulsory).

Such thresholds are defined as being based on domain knowledge

$$f(a) = \begin{cases} \text{immature, if } a < a_{\min} \forall w < w_{\min} \\ \text{overmature, if } a \geq a_{\max} \\ \text{Ready to Harvest, if } a_{\min} \leq a \leq a_{\max} \forall w \geq w_{\min} \end{cases} \quad (12)$$

The last rule based classification functionality is given as:

$$f_{\text{rule}}(x) = \begin{cases} \text{Grade C (immature), } a < 10 \vee w < 1.2 \\ \text{Reject (over mature), } a > 14 \\ \text{pass to ML, otherwise} \end{cases} \quad (13)$$

Stage 2 – ML-based classification

The ambiguous samples, which need further analysis, are only subjected to a supervised ML classifier (Random Forest).

For ambiguous samples:

$$x' = [w, d, a, c, h, r] \quad (14)$$

where other features can consist of:

h exposure to humidity and r fresh rain-fall.

ML classifier

Random forest (RF) classifier is trained:

$$y' = f_{ML}(x') \quad (15)$$

Where,

$$y' \in \{\text{Grade A, Grade B, Grade C}\} \quad (16)$$

Random Forest decision

RF makes predictions based on majority voting:

$$y' = \text{mode}\{T_1(x'), T_2(x'), \dots, T_n(x')\} \quad (17)$$

The trees T_i are trained to nonlinearly predict the relationship between physical and environmental features.

Confidence based decision making can be supported using the output probabilities. The calculation is possible using the following equation.

$$P(y = k|x') \forall k \in \{A, B, C\} \quad (18)$$

3.4 Demand Forecasting and market clustering

The various markets show high demand of coconuts because of variation in consumption behavior, seasonal elasticity, distance to the farms of coconuts and preferences of the purchasers [19].

Single global demand model training is a way of ignoring this heterogeneity, and training a model per market can have a lack of data. To deal with this, CMF uses similar clusters of markets and trains a single lightweight model in each cluster, which balances accuracy and simplicity.

Every market m is characterized by a feature vector.

$$z_m = \begin{bmatrix} \mu_p^m \\ \sigma_p^m \\ \mu_d^m \\ \sigma_d^m \\ \text{Dist}_m \end{bmatrix} \quad (19)$$

where:

μ_p^m : mean price trend

σ_p^m : price volatility

μ_d^m : average demand

σ_d^m : demand variability

$Dist_m$: distance from production zone

Clusters of markets are made in such a way that similarity within clusters is maximized and dissimilarity between clusters is minimized. The market clustering k-means algorithm is applied below:

$$\min_C \sum_{k=1}^K \sum_{m \in C_k} \|z_m - \mu_k\|^2 \quad (20)$$

Where,

C_k is the k-th market cluster

μ_k is the centroid of cluster C_k .

The distance between cluster is made by computing the distance measure as below:

$$\|z_i - z_j\| = \sqrt{\sum_{l=1}^L (z_{i,l} - z_{j,l})^2} \quad (21)$$

3.5 Price Prediction

QXGB predicts price uncertainty using multiple conditional quantiles as opposed to a single expected price.

For market m at time t :

$$X_{m,t} = [D_{m,t}, P_{m,t-1}, R_t, T_t S_t] \quad (22)$$

where:

D : demand forecast

P : past prices

R, T : rainfall, temperature

S : supply availability

3.6 Inventory and storage Decision

Convert forecasts into a direct policy decision: Store or Sell based on the decision rule defined below:

$$Action = \begin{cases} Store, & S_{PL} > \theta \\ Sell, & otherwise \end{cases} \quad (23)$$

S_{PL} is a Profit-loss score can be computed through store and sell function that is defined below.

$$S_{PL} = \Pi_{store} - \Pi_{sell} \quad (24)$$

Where,

Π_{store} = expected profit from storing the coconut harvest for a future period

Π_{sell} = expected profit obtained by selling the coconut harvest immediately

3.7 Logistic Route Optimization

Make realistic predictions of travel time and incorporate it in classical routing. Optimized route can be calculated using the algorithm of random Forest. Following equation may be used to predict the delay in route:

$$T'_{ij} = f_{RF}(d_{ij}, r_{ij}, w_t, rain_t) \quad (25)$$

d_{ij} - distance, r_{ij} : road type, w_t : weather,

Algorithm 2: Supply Chain optimization of coconut – COCOSMART

Step 1: Gather real-time and past data of all the stakeholders

Step 2: Source reliability estimation (WSRE preparation)

Assess the quality of every source of data by verifying:

the extent of data loss, the time-varying consistency of the values, its comparison with references of trusted information (e.g. intake records in the warehouse and records of the farmer, market average in the region and records of it at home).
Give a credibility rating to every source.

Step 3: Reliability-weighted data integration (WSRE)- Integrate all sources into a single one.

Step 4: Missing data treatment and data cleaning with SSI.

Forced to identify missing records (price, demand, harvest quantity, etc.).

Impute missing values by:

- getting preceding weeks of the past years with the same season,
- choosing weeks that have the same rain and temperature,
- completion filling of the missing value by the weighted average of the similar historical weeks.

Step 5: Quality grading and harvest readiness

- Grading of coconut quality is to be done in two stages:
- Stage 1: use simple threshold rules (age, weight, size) to identify blatant cases (immature/ready/over-mature).
- Stage 2: grade final in uncertain cases by classifying the cases with a light weight ML classifier (Random Forest).

Step 6: Market clustering demand forecasting (CMF).

Divide the markets into groups according to similarity in:

- price trend,
- demand pattern,
- geographic distance and logistics behavior.

This will assure that similar markets have identical demand forecasting model.

Step 7: Demand prediction (Model training and prediction)

Train a small regression model (e.g. XGBoost) on one market cluster, and predict future demand on markets in that cluster.

Step 8: Price prediction with risk estimation (QXGB)

XGBoost quantile-based train models to predict:

- lower price bound (10th percentile),
- median expected price (50th percentile),
- high price limit (90th percentile).

Calculate risk / volatility band as upper bound- lower bound

Step 9: Inventory and storage decision-making (PLSM)

To calculate a store-vs-sell decision of each farmer, calculate it on the basis of:

- anticipated current selling profit,
- profit on future selling of,
- storage cost,
- spoilage risk,
- demand conditions.

Generate a storage recommendation when it is expected that the payoff of storing would be greater than the payoff of selling at this stage.

Step 10: Logistics planning using ML-assisted routing (MARP)

Make predictions of the real time/delay of travel based on the model (Random Forest) of machine learning along with the road type, distance, rain, and other proxies.

Take these estimated times as weights of the routes and use some classical routing solver (shortest path / VRP) to choose the optimal delivery route.

Step 11: Farmer-buyer matching with fairness (F-kNBM)

- For each farmer's produce lot:
- Shortlist and select the top-k appropriate buyers in terms of the price offered, distance, grade requirement, and reliability.
- assign lots with a fairness limit that ensures that large lots do not buy up the capacity before the small ones can have a good lot.

Step 12: Recommendation generation (SRE)

Combine outputs from:

- demand forecast,
- price forecast,
- delay prediction,
- buyer matching,
- store/sell decision

into a single scoring system to rank the actions.

Develop the ultimate recommendations:

- best market,
- best time to sell,
- best buyer,
- best route,
- quantity to be stored and duration of storing

Step 13: Marketing performance impact evaluation (PS-MLU)

Assess the actual effects of the adoption of AI by:

- matching adopters and non-adopted with propensity scores,
- uplift (gain) in the marketing performance results including:
- realization of prices, profit, market access, and minimized losses.

Final deliverables

- Recommendations to farmers: sell/store/where/when/how.
- Streamlined routing and buyer distribution strategy.
- Quantitative changes in marketing performance.

4. Result Analysis and Discussion

The framework of the suggested AI-based supply chain optimization was tested with the help of combined datasets that included records of harvests of farmers, market prices, buyer demands, weather conditions, logistics conditions, and storage information [20]. Each of the modules was evaluated on its own and as a cohesive group to examine how each of the modules would contribute to the overall performance of the marketing of the coconut farmers. Predictive accuracy and decision-level effectiveness were equally taken into account.

4.1 Quality grading and harvest readiness results

The Two-Stage Rule + ML (TRML) classifier was able to provide high grading accuracy through the use of expertise and machine learning. The rule-based filtering had been effective in getting rid of blatant immature and over-mature samples and minimized the classification load on the ML model.

- Classification accuracy
- Precision
- Recall
- F1-score

i. Accuracy

Measurement of quality grading performance was done on standard classification measures which are as follows:

Accuracy is used to measure the general correctness of the classification.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (26)$$

ii. Precision

The ratio of the number of coconuts that is correctly classified as a particular quality grade to the total coconuts that are predicted to be of that quality grade is referred to as precision.

$$Precision = \frac{TP}{TP+FP} \quad (27)$$

iii. Recall

The element of recall is used to determine how well the classifier will recognize all coconuts of a specific grade.

$$Recall = \frac{TP}{TP+FN} \quad (28)$$

iv. F1-Score

The F1-score provides a balanced measure between precision and recall.

$$F1 - Score = 2 \cdot \frac{Precision \times Recall}{Precision + Recall} \quad (29)$$

Table 1: Overall Result comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Rule based grading	78.6	76.4	74.9	75.6
Stand alone ML	86.9	85.1	84.3	84.7
Proposed TRML	92.4	91.1	90.3	90.7

Conventional rule-based grading method performed least in all the measures of evaluation because it could be used to draw only limited straight line relationships among the attributes of coconut quality and because it was sensitive to set limits and to environmental change. The standalone machine learning models which enhanced the grading accuracy by learning intricate patterns of data were influenced by noisy samples and the boundary case, which resulted in a decline in interpretability and classification uncertainty. However, the suggested TRML framework outperformed them with an accuracy improvement of around 5.5 and 13.8 over the standalone ML models and rule-based approaches respectively. This enhancement is largely due to its hybrid nature, with rule-based filtering of the exit cases, and the ML classifier being allowed to concentrate on the ambiguous ones so that it can lead to increased precision and recall, and overall robust grading.

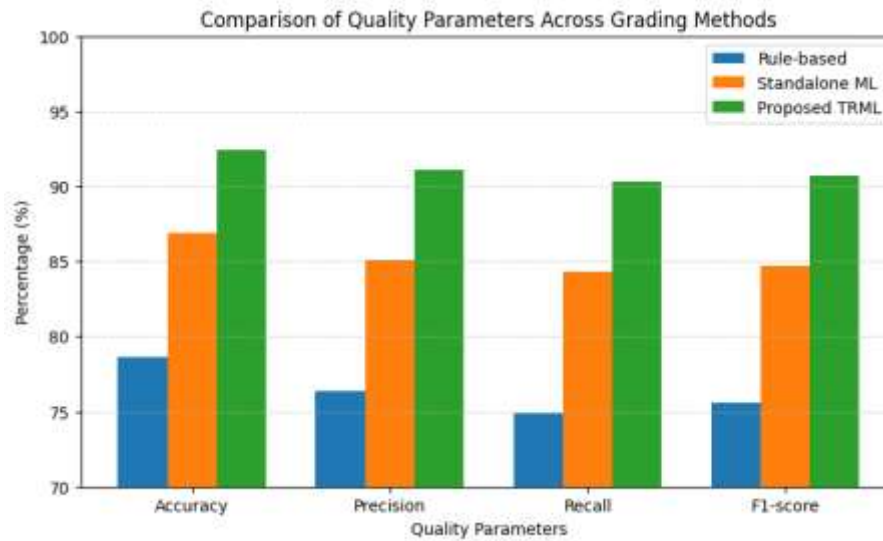


Figure 1: Comparison of Quality parameters

4.2 Demand Forecasting Performance

The proposed CMF method proves to be significantly smaller in terms of its forecasting errors in all evaluation measures, than the single global model. The demand on the product on the market is predicted using the following metrics.

i. Mean Absolute Error

Mean Absolute Percentage Error (MAPE) is an absolute percentage ratio of predicted and realized values averaging and is a scale-free statistic that can be used to compare, similar to different markets or different levels of demand.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - y'_i| \quad (30)$$

ii. Root Mean Square Error (RMSE)

The suggested CMF model shows a significant reduced forecasting errors in all assessment metrics as compared to the single global model.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y'_i)^2} \quad (31)$$

where:

y_i is the actual demand value,

y'_i is the predicted demand value,

n is the total number of observations.

iii. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is used to gauge the mean absolute percentage error of the predictions and the true value, so that it is a scale-independent measure, and can be used to compare markets or levels of demand across different markets.

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - y'_i}{y_i} \right| \quad (32)$$

Table 2: Result Comparison

Metric	Single Global Model	Proposed CMF
MAE	18.5	12.1
RMSE	24.2	16.7
MAPE	15.8	9.6

Table 2 and Figure 2, which propose CMF approach, show significant reduction of forecasting errors of all measures of evaluation compared to a single global model. The decrease in MAE and RMSE shows an increase in accuracy and strength of the demand estimation and the lower MAPE is made by the better relative prediction results with different levels of demand. The increase can be explained by the fact that markets with similar demand and price patterns are clustered together, and thus cluster-specific models are able to exploit local and seasonal patterns better than a generalized forecasting method.

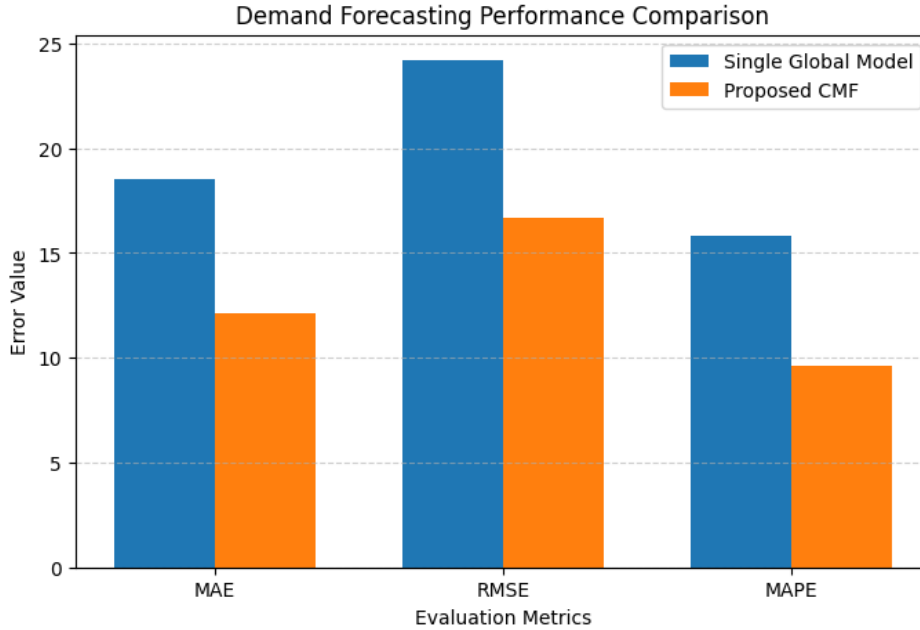


Figure 2: performance comparison of Demand forecasting

4.3 Logistics and routing Optimization results

The proposed ML-Assisted Route Prioritization (MARP) approach was compared to a traditional distance-based route prioritization method in terms of its performance. MARP combines travel time prediction, an approach that uses machine-learning to predict travel time, with classical shortest-path routing and allows more realistic and adaptable logistics planning in the changing road and weather conditions.

i. Average delivery time

Average delivery time- It is the average time of transporting coconut consignments between farms and markets.

$$\text{Average delivery time} = \frac{1}{n} \sum_{i=1}^n T_i \quad (33)$$

Where, T_i is the time required to deliver the $i - th$ shipment and n is the number of deliveries.

ii. Delay Reduction rate

Delay reduction rate This is the percentage change in delivery time between MARP and base routing.

$$\text{Delay Reduction (\%)} = \frac{T_{\text{baseline}} - T_{\text{MARP}}}{T_{\text{baseline}}} \times 100 \quad (34)$$

iii. Transportation cost savings

Delay reduction rate: This is a percentage change in time of delivery which MARP has over baseline routing.

$$\text{Cost Savings (\%)} = \frac{C_{\text{baseline}} - C_{\text{MARP}}}{C_{\text{baseline}}} \times 100 \quad (35)$$

C represents transportation cost.

Table 3: Performance Comparison of Route optimization

Metrics	Distance based Routing	Proposed MARP
Average delivery time (min)	95	68
Delay Reduction (%)	0	28.4
Transportation Cost Savings (%)	0	18.6

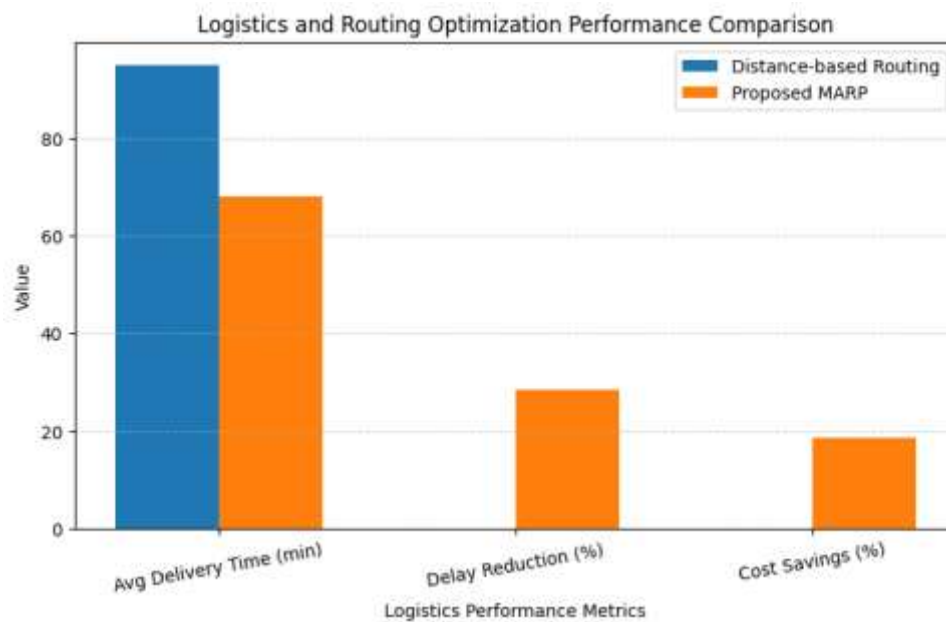


Figure 3: Performance comparison of Routing optimization

Figure 3 and table 3 above indicate the results of the route optimization. The improved results can be primarily attributed to the fact that MARP can integrate the predicted travel time -the result of learning using the past logistics, road conditions, and weather information - into the classical routing algorithms. As compared to distance-based routing that considers equal travelling conditions, MARP is more dynamic to real world variability resulting in quicker deliveries and less fuel burn. These findings support the idea that lightweight machine learning models will significantly complement the traditional optimization of logistics without the difficulty of reinforcement learning methods.

5. Conclusion

This paper proposed an artificial intelligence-based supply chain optimization model to improve the marketing performance of the coconut farmers in terms of data-driven decision support. The offered methodology combined reliability-conscious data fusion, seasonality-conscious data preprocessing, hybrid quality grading, clustered demand forecasting, and price prediction that is aware of uncertainties, profit-oriented inventory control, and inventory optimization with the help of ML, as well as equitable farmer-buyer matching. The efficacy of the framework in several stages of supply chain was exhibited by experimental results. The Two-Stage Rule + ML (TRML) classifier had a grading

accuracy of 92.4 percent which is much higher compared to the traditional rule-based and standalone machine learning methods. The Clustered Market Forecasting (CMF) model decreased the errors in demand forecasting with low MAE, RMSE, and MAPE than when using a single global model. Also, ML-Assisted Route Prioritization (MARP) strategy shortened the average delivery time by 28.4% with a delay cut of 28.4% and transportation cost cut of 18.6%. In general, in these findings, the authors confirm that the integration of simple but new machine learning styles with the domain knowledge can greatly enhance price realization, reduce post-harvest losses, and increase accessibility of the markets to the coconut farmers. The offered framework is viable, explainable, and can be implemented on a large scale, implying that it can be utilized in the real-world agri-marketing optimization application and offers a robust starting point to future studies in the field.

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