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A Predictive Study on Cardamom Production Trends in Nepal: Using Machine Learning Techniques

by

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The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a thesis entitled **"A Predictive Study on Cardamom Production Trends in Nepal: Using Machine Learning Techniques"** submitted by Sonal Man Singh in partial fulfilment of the requirements for the degree of Master of Science in Engineering in Technology and Innovation Management.

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Sonal Man Singh

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ABSTRACT

Cardamom is an important cash crop and a major agricultural export of Nepal. However, its production is greatly influenced by weather conditions, soil quality, market demand, and farming methods, causing changes in yield and prices. Traditional prediction methods have struggled to provide accurate estimates, making it difficult for farmers to plan effectively. This study applies machine learning techniques to predict cardamom production in Nepal, aiming to create a reliable forecasting model that can help farmers, traders, and policymakers make informed decisions. The research used historical cardamom production data from Mendeley Data and tested three machine learning models Random Forest, XGBoost, and Gradient Boosting to develop an effective prediction system. The dataset was prepared by cleaning and organizing the data, selecting key factors, and dividing it into training and testing sets. The models were assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score to measure prediction accuracy. Additional analyses, such as feature importance ranking, confusion matrices, and AUC-ROC curves, were used to evaluate model performance.

The results showed that Random Forest gave the most accurate predictions, achieving an R^2 score of 97.7 percent, followed by Gradient Boosting (96.63 percent) and XGBoost (94.96 percent). The most important factors influencing production were the previous year's yield, growth rate, and year, proving that past production trends are highly useful in forecasting. However, some challenges were identified, including the lack of real-time climate data, limited awareness and use of AI tools among farmers, and the absence of government policies to support AI-based agricultural predictions.

To overcome these challenges, the study recommends setting up an AI-based monitoring system to track production and climate conditions, improving data collection and sharing, using AI for market forecasting, and developing easy-to-use AI tools for farmers. This research highlights the potential of machine learning in transforming Nepal's agricultural sector by improving production forecasts and helping stakeholders make better decisions.

Keywords: *Cardamom production, machine learning, Random Forest, XGBoost, Gradient Boosting, agricultural forecasting, AI in agriculture, Nepal.*

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LIST OF ABBREVIATIONS

ML	: Machine Learning
AI	: Artificial Intelligence
RF	: Random Forest
XGBoost	: Extreme Gradient Boosting
ARIMA	: Autoregressive Integrated Moving Average
SARIMAX	: Seasonal ARIMA with Exogenous variables
MAE	: Mean Absolute Error
RMSE	: Root Mean Squared Error
AUC-ROC	: Area Under the Receiver Operating Characteristic
DTs	: Decision Trees
GBM	: Gradient Boosting Machine
SVMs	: Support Vector Machines
GPs	: Gaussian Processes
MLPs	: Multilayer Perceptrons
CNNs	: Convolutional Neural Networks
RNNs	: Recurrent Neural Networks
PCA	: Principal Component Analysis

CHAPTER ONE: INTRODUCTION

1.1 Background

Large cardamom (*Amomum subulatum*) is a vital cash crop in Nepal, significantly contributing to the country's agrarian economy. Nepal stands as the world's largest producer of large cardamom, accounting for approximately 68% of the global market share, followed by India (22%) and Bhutan (9%) (Shrestha et al., 2018). The primary cultivation regions are the eastern hilly districts, notably Taplejung, Panchthar, Ilam, and Sankhuwasabha, which collectively contribute over 80% of the national production (Shrestha et al., 2018).

Despite its prominence, the cardamom industry in Nepal faces several challenges. Production fluctuations have been observed, with outputs recorded at 9,545 tons in 2019-20, decreasing to 8,289 tons in 2020-21, and slightly increasing to over 10,000 tons in 2022-23 (The Kathmandu Post, 2024). Factors contributing to these inconsistencies include climate change, pest infestations, and diseases, which adversely affect yield and quality. For instance, in Taplejung, a significant decline of up to 60% in production was reported due to pest invasions in hilly terrains (Commodity Board, 2024).

In response to these challenges, the integration of advanced technologies, particularly machine learning (ML), into agricultural practices has gained traction. ML offers robust tools for analyzing complex datasets, enabling accurate predictions and informed decision-making. Studies have demonstrated the efficacy of ML models in forecasting agricultural outputs, optimizing resource allocation, and enhancing overall productivity (Khaki and Wang, 2019). For example, the application of ML techniques has been explored in predicting cardamom prices, assisting farmers in making strategic decisions regarding cultivation and sales (Kuriakose et al., 2021).

This study aims to harness machine learning methodologies to develop a predictive model for large cardamom production in Nepal. By analyzing historical production data alongside climatic and environmental variables, the model seeks to provide accurate forecasts, thereby equipping farmers, policymakers, and stakeholders with the insights necessary to navigate the complexities of cardamom cultivation and market dynamics.

1.2 Problem Statement

Large cardamom (Amomum subulatum) is a critical cash crop in Nepal, contributing significantly to the agricultural economy and international exports. Nepal remains the world's largest producer, accounting for nearly 68% of the global supply (Shrestha et al., 2018). However, cardamom production faces unpredictable fluctuations due to several factors, including climate change, pest infestations, soil conditions, and market dynamics (The Kathmandu Post, 2024). These uncertainties make it difficult for farmers, policymakers, and exporters to make informed decisions about cultivation, resource allocation, and trade.

Traditional forecasting methods rely on historical trends, expert judgment, and manual estimations, which often fail to capture complex relationships between various factors affecting production. As a result, there is a lack of accurate and data-driven forecasting models that can help farmers anticipate yield variations and prepare accordingly. In recent years, machine learning (ML) techniques have proven effective in agricultural predictions, allowing for pattern recognition, trend analysis, and predictive modeling (Khaki and Wang, 2019). By utilizing ML, stakeholders can benefit from precise production forecasts, enabling better planning, reduced economic risks, and sustainable agricultural development.

This study aims to develop a machine learning-based predictive model to estimate large cardamom production in Nepal. By analyzing historical production data, climatic variables, and economic trends, this research will provide a data-driven approach to forecasting production. The findings will offer valuable insights for farmers, policymakers, and researchers to enhance decision-making, resource management, and market strategies.

1.3 Research Questions

To achieve the study’s objectives, the following research questions are addressed:

1. What are the major factors affecting large cardamom production in Nepal?
2. How can machine learning models be applied to predict cardamom production trends accurately?

3. Which machine learning model (Random Forest, XGBoost, or Gradient Boosting) provides the most accurate forecasts for large cardamom production?
4. How effective are these machines learning models in comparison to traditional forecasting methods?
5. What practical recommendations can be derived from predictive insights to support Nepalese farmers and policymakers?

1.4 Research Objectives

1.4.1 Main Objective

The primary objective of this study is to develop a machine learning-based predictive model to forecast large cardamom production in Nepal.

1.4.2 Specific Objectives

The study specifically aims to:

- Analyze historical trends in large cardamom production and identify key factors influencing yield fluctuations, such as climate, pests, and market conditions.
- Develop and compare machine learning models (Random Forest, XGBoost, and Gradient Boosting) for cardamom production prediction.
- Evaluate model performance using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 score.
- Explore the feasibility of implementing predictive analytics to assist farmers, policymakers, and stakeholders in making informed agricultural decisions.
- Provide recommendations based on model findings to improve the sustainability and economic stability of large cardamom farming in Nepal.
- Compare large cardamom production forecasts with export forecasts, analyzing discrepancies to optimize production planning and export strategies.

1.5 Significance of the Study

This study is significant as it applies machine learning to predict large cardamom production in Nepal, benefiting multiple stakeholders:

- For Farmers – Helps in crop planning, risk management, and market decision-making through accurate yield predictions.
- For Policymakers – Supports evidence-based agricultural policies, resource allocation, and climate adaptation strategies.
- For Exporters & Market Analysts – Improves supply chain efficiency, stabilizes market prices, and enhances Nepal's global competitiveness in cardamom exports.
- For Researchers – Contributes to AI-driven agricultural innovations, serving as a benchmark for future studies on predictive analytics in farming.

By bridging traditional forecasting methods with machine learning, this study enhances decision-making, sustainability, and economic stability in Nepal's cardamom industry.

CHAPTER TWO: LITERATURE REVIEW

2.1 Cardamom Production in Nepal

Nepal is the world's leading producer of large cardamom (Amomum subulatum), contributing approximately 68% of the global market supply (Shrestha et al., 2018). The primary cultivation regions include the eastern hilly districts, notably Taplejung, Panchthar, Ilam, and Sankhuwasabha, which collectively contribute over 80% of Nepal's total production (The Kathmandu Post, 2024). Large cardamom is not only a high-value cash crop but also an essential export commodity, with major markets in India, the Middle East, and Europe (Commodity Board, 2024).

Despite its economic significance, cardamom production in Nepal has been highly volatile, with notable fluctuations in yield due to climate change, pest infestations, and changing market prices (MoALD, 2023). Reports indicate that Nepal's cardamom production fell from 9,545 tons in 2019-20 to 8,289 tons in 2020-21 due to these challenges, before slightly recovering in 2022-23 (The Kathmandu Post, 2024). This unpredictability in production affects farmers' incomes, supply chain stability, and Nepal's export competitiveness.

In response to these uncertainties, advanced agricultural forecasting methods have gained attention, particularly in the form of machine learning models that provide data-driven predictions for crop production (Khaki & Wang, 2019). This chapter explores the factors influencing cardamom production, existing traditional forecasting methods, and existing research gaps in the field.

2.2 Factors Affecting Cardamom Production

Cardamom production is influenced by multiple environmental, biological, and economic factors. Understanding these factors is crucial for improving forecasting accuracy and developing effective predictive models.

2.2.1 Climate and Weather Conditions

Climate plays a crucial role in large cardamom farming, as it thrives in subtropical to temperate climates at elevations between 600–2,000 meters. Research indicates that ideal conditions include temperatures between 10°C–20°C and annual rainfall between 1,500–2,500 mm (ICIMOD, 2022).

However, erratic climate patterns, unseasonal rainfall, and prolonged droughts have led to reduced yields and increased vulnerability to diseases (Shrestha et al., 2018). Studies have shown that temperature increases by even 1°C above normal reduce yield by 10-15% (Khadka et al., 2021). Therefore, climate data must be integrated into predictive models to improve forecasting accuracy.

2.2.2 Soil Quality and Nutrient Management

The fertility of acidic, well-drained loamy soil significantly influences cardamom growth. Soil quality deterioration due to deforestation, soil erosion, and improper fertilization affects plant health and yield (Bhattarai & Maharjan, 2020). The application of organic manure and biofertilizers has been found to increase productivity by up to 20% (Subedi et al., 2022).

2.2.3 Pests and Diseases

Pests such as white grubs, leaf-caterpillars, and thrips are known to cause severe yield losses in cardamom plantations (ICIMOD, 2022). Additionally, fungal infections like Colletotrichum blight and Fusarium wilt have been reported in Nepal, leading to a decline in production by nearly 40% in affected regions (MoALD, 2023).

Predictive models that incorporate pest outbreak data and climate factors can help farmers take preventive measures in advance, reducing losses.

2.2.4 Economic and Market Influences

Cardamom prices are highly volatile, impacting farmers' decision-making on cultivation, storage, and sales. Historical data shows that prices peaked at USD 28/kg in 2014 but dropped to USD 10/kg in 2017, severely affecting farmers' incomes (The Kathmandu Post, 2024).

Machine learning models have been successfully applied in agricultural price forecasting, enabling farmers to make informed decisions on when to sell their crops (Kuriakose et al., 2021).

2.3 Traditional Forecasting Methods in Agriculture

Traditional agricultural forecasting techniques are based on statistical models and expert judgment. While they provide basic yield estimations, they often fail to capture complex, non-linear relationships in data.

2.3.1 Time Series Analysis

Time series models, such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing, have been widely used for crop yield forecasting (Tripathi et al., 2020). However, these models rely on historical trends and do not adapt well to sudden climate or economic changes.

2.3.2 Regression-Based Models

Linear regression models are commonly applied to predict agricultural yields based on climate, soil, and input usage data (Ghosh et al., 2019). However, they struggle with multi-variable dependencies and complex interactions.

2.3.3 Limitations of Traditional Methods

- Inability to handle large, unstructured data (e.g., satellite imagery, real-time weather data).
- Limited adaptability to rapid environmental changes.
- Lower prediction accuracy compared to machine learning models.

2.4 Research Gaps

Despite the growing research on agricultural yield forecasting, several gaps exist in applying machine learning to cardamom production prediction.

2.4.1 Limited Application of Machine Learning in Cardamom Production

Most machine learning studies focus on major crops like wheat, rice, and maize (Khaki & Wang, 2019). Limited research exists on applying ML models to high-value cash crops like cardamom.

2.4.2 Lack of Integration of Multiple Data Sources

Current yield prediction models often use historical production data alone, neglecting real-time climate, pest outbreaks, and soil quality data (Tripathi et al., 2020). Integrating multiple factors could improve model accuracy.

2.4.3 Lack of Comparative Studies Between ML and Traditional Models

There are few comparative analyses evaluating whether machine learning models outperform traditional forecasting methods in cardamom prediction (Ghosh et al., 2019). A structured comparison could highlight the strengths and weaknesses of each approach.

2.4.4 Practical Implementation Challenges

While ML models can provide high accuracy, their real-world adoption by farmers remains low due to limited access to technology, computational resources, and user-friendly forecasting tools (Kuriakose et al., 2021). More research is needed on developing simple, accessible ML-based prediction systems.

2.5 Research Gaps and Their Connection to the Problem Statement & Objectives

The identified research gaps directly inform the problem statement and research objectives, highlighting the need for a machine learning-based predictive model for cardamom production in Nepal. These gaps shape the direction of the study, ensuring that it addresses real-world challenges faced by farmers, policymakers, and researchers.

2.5.1 How Research Gaps Relate to the Problem Statement

In the problem statement, the study highlights key issues in cardamom production prediction, emphasizing challenges such as climate change, yield unpredictability, and limitations of traditional forecasting methods. Below is a direct link between these research gaps and the problem statement:

Table 1 How Research Gaps Relate to the Problem Statement

Research Gap	How It Relates to the Problem Statement
Limited Application of Machine Learning in Cardamom Production	The problem statement highlights that existing traditional forecasting methods are inaccurate and outdated, and no ML-based predictive model has been developed specifically for cardamom in Nepal.
Lack of Integration of Multiple Data Sources	The study addresses the need for a comprehensive ML model that incorporates historical yield, climate, soil conditions, and pest infestations for better predictions.
Lack of Comparative Studies Between ML and Traditional Models	The study aims to compare ML models (Random Forest, XGBoost, Gradient Boosting) with traditional statistical models (ARIMA, regression) to determine which approach is superior.
Practical Implementation Challenges	The problem statement highlights the lack of user-friendly ML tools for farmers and policymakers, which this study aims to resolve.

These research gaps justify the need for a machine learning model that is data-driven, accurate, and capable of real-time forecasting to address production uncertainties and economic risks.

2.5.2 How Research Gaps Shape the Research Objectives

The study's objectives are directly influenced by the identified research gaps, ensuring that the research addresses existing shortcomings and contributes new knowledge to the field.

Table 2 How Research Gaps Shape the Research Objectives

Research Gap	Corresponding Research Objective
Limited Application of Machine Learning in Cardamom Production	**Objective 1**: To analyze historical trends in large cardamom production and identify key influencing factors.
Lack of Integration of	**Objective 2**: To develop and implement machine

Multiple Data Sources	learning models (Random Forest, XGBoost, and Gradient Boosting) incorporating multiple data sources (climate, pests, soil conditions, etc.).
Lack of Comparative Studies Between ML and Traditional Models	**Objective 3**: To evaluate and compare machine learning models with traditional forecasting techniques based on accuracy and efficiency.
Practical Implementation Challenges	**Objective 4**: To explore the feasibility of implementing predictive analytics for practical use by farmers and policymakers.
Improving Agricultural Decision-Making	**Objective 5**: To provide actionable recommendations based on the predictive findings to support sustainable cardamom production in Nepal.

Each objective is aligned with a research gap, ensuring that the study not only contributes to academic knowledge but also provides real-world solutions for stakeholders.

2.5.3 Conclusion and Importance of Addressing These Gaps

Addressing these research gaps is crucial for developing a more reliable and robust prediction model for cardamom production. By integrating machine learning with real-time data sources, the study will enhance yield predictability, reduce risks, and help farmers optimize decision-making. The findings will also provide valuable insights for policymakers, enabling them to develop data-driven agricultural policies to support Nepal's cardamom industry.

2.6 Machine Learning Models

Machine Learning (ML) models are algorithms that learn patterns from data to make predictions or decisions without explicit programming (Mitchell, 1997). Their adoption has exploded due to increasing computational power, big data availability, and algorithmic innovations (Jordan & Mitchell, 2015). ML models are broadly classified into:

- **Supervised Learning** (e.g., classification, regression),
- **Unsupervised Learning** (e.g., clustering, dimensionality reduction),
- **Reinforcement Learning** (e.g., autonomous decision-making).

2.7 Key Machine Learning Models and Their Theoretical Foundations

2.7.1 Linear Models

- **Linear Regression (LR)**: One of the oldest predictive models, based on least squares estimatio. Modern adaptations (e.g., Ridge/Lasso regression) introduce regularization to prevent overfitting.
- **Logistic Regression (LogR)**: Despite its name, LogR is a classification model that estimates probabilities using the logistic function. It remains widely used in medicine and social sciences due to interpretability.
- **Limitations**: Assumes linear decision boundaries; struggles with high-dimensional, nonlinear data.

2.7.2 Tree-Based Models

- **Decision Trees (DTs)**: Use recursive binary splitting (Breiman et al., 1984). Prone to overfitting, leading to ensemble methods.
- **Random Forest (RF)**: An ensemble of decorrelated trees via bagging (Breiman, 2001). Robust to noise but lacks interpretability.
- **Gradient Boosting Machines (GBM)**: Sequentially corrects errors using gradient descent (Friedman, 2001). XGBoost (Chen & Guestrin, 2016) and LightGBM (Ke et al., 2017) improved efficiency via parallelization and histogram-based splits.
- **CatBoost**: Optimized for categorical data with ordered boosting.

2.7.3 Kernel-Based Models

- **Support Vector Machines (SVMs)**: Maximize margin between classes using kernel tricks. Effective for small datasets but computationally expensive for large-scale problems.
- **Gaussian Processes (GPs)**: Bayesian nonparametric models for regression.

2.7.4 Neural Networks and Deep Learning

- **Multilayer Perceptrons (MLPs)**: Universal function approximators.
- **Convolutional Neural Networks (CNNs)**: Dominant in computer vision.
- **Recurrent Neural Networks (RNNs)**: Handle sequential data.
- **Transformers**: Self-attention mechanisms revolutionized NLP (e.g., BERT, GPT-3).

2.7.5 Unsupervised Learning Models

- **k-Means Clustering**: Iterative centroid-based partitioning.
- **Principal Component Analysis (PCA)**: Linear dimensionality reduction.
- **Generative Models**: GANs (Goodfellow et al., 2014) and VAEs (Kingma & Welling, 2014) for synthetic data generation.

2.8 Comparative Analysis of ML Models

Table 3 Comparative Analysis of ML Models

Model	Strengths	Weaknesses	Best Use Cases
Linear Regression	Interpretable, fast	Poor for nonlinear data	Econometrics, causal inference
Random Forest	Handles high-dimensional data well	Black-box nature	Bioinformatics, remote sensing
XGBoost	State-of-the-art for tabular data	Hyperparameter sensitivity	Kaggle competitions, finance
SVM	Effective in high-dimensional spaces	Slow for large datasets	Text classification, genomics
Deep Learning	SOTA for unstructured data (images, text)	Data-hungry, computationally heavy	Computer vision, NLP

2.9 Random Forest (RF) Model

Random Forest (RF), introduced by Leo Breiman (2001), is an ensemble learning method that constructs multiple decision trees during training and outputs the mode (classification) or mean (regression) of individual trees. It is renowned for:

- High accuracy with minimal hyperparameter tuning.
- Robustness to noise and overfitting.
- Feature importance estimation.

RF is widely used in bioinformatics, remote sensing, finance, and healthcare due to its versatility (Liaw & Wiener, 2002).

RF represents one of the most influential machine learning algorithms developed in the early 21st century, fundamentally changing how we approach complex prediction problems. At its core, RF is an ensemble learning method that operates by constructing a multitude of decision trees during training and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. What makes RF particularly remarkable is its elegant synthesis of simplicity and power, combining intuitive concepts from statistics and computer science to create a robust prediction framework.

The theoretical foundation of RF rests on several key principles that collectively explain its exceptional performance across diverse domains. First is the concept of ensemble learning itself - the idea that multiple weak learners can combine to form a strong learner. This draws inspiration from the statistical principle that the variance of an average decreases as more observations are included. In RF, each decision tree acts as a weak learner, and their aggregation through voting or averaging leads to substantially improved predictive accuracy and stability compared to single trees. The algorithm ingeniously addresses the primary weakness of individual decision trees - their tendency to overfit training data - by introducing randomness at two levels: in the data samples used to build each tree and, in the features, considered for splitting at each node.

A deeper theoretical examination reveals that RF operates through what might be called "controlled randomness." While each tree is allowed to grow with minimal pruning (typically to maximum depth), the random selection of both training subsets and splitting features ensures that the trees in the forest remain diverse. This diversity is crucial because it means the errors made by individual trees are unlikely to be correlated. When these uncorrelated errors are averaged across many trees, they tend to cancel each other out, leading to predictions with reduced variance. This mechanism mirrors the statistical concept of the law of large numbers, where aggregation leads to more stable and reliable outcomes.

The theoretical beauty of RF also lies in its dual nature as both a predictive model and an exploratory tool. Beyond making accurate predictions, RF provides intrinsic measures of variable importance, offering insights into which features contribute most significantly to predictive performance. This emerges naturally from the algorithm's

structure, as features that consistently provide better splits across many trees are identified as more important. This feature importance measure has become invaluable in domains where understanding variable contributions is as important as prediction accuracy itself, such as in biomedical research or social sciences.

From a computational complexity perspective, RF presents an interesting case study. While building numerous deep trees might seem computationally intensive, the algorithm's inherent parallelism (each tree can be built independently) makes it highly scalable. Furthermore, the random feature selection at each split reduces the computational burden compared to methods that evaluate all features at every opportunity. This combination of predictive power and computational efficiency has contributed to RF's widespread adoption in both academic research and industrial applications.

The theoretical framework of RF also helps explain its robustness to common data issues that plague other algorithms. The random sampling of data points means that RF is naturally resistant to outliers - no single data point can exert undue influence across all trees. Similarly, the algorithm handles missing values gracefully, as the splitting criteria can proceed using available data without requiring imputation. These properties emerge directly from RF's theoretical construction rather than requiring additional engineering solutions.

As we continue to push the boundaries of machine learning, RF remains a benchmark method due to its solid theoretical foundations. Its success has inspired numerous variants and extensions, each building on the core principles while addressing specific limitations. The algorithm's theoretical clarity, combined with its practical effectiveness, ensures that RF will remain an essential tool in the machine learning toolbox for the foreseeable future, continuing to provide insights into both the nature of our data and the behavior of ensemble methods more generally.

2.10 XGBoost (Extreme Gradient Boosting) Model

XGBoost represents a significant advancement in the field of gradient boosting algorithms, emerging as one of the most powerful machine learning techniques for

structured data problems. Developed by Tianqi Chen and Carlos Guestrin in 2016, XGBoost builds upon the traditional gradient boosting framework while introducing several key innovations that enhance its computational efficiency, predictive performance, and scalability. The algorithm has become particularly renowned for its dominance in machine learning competitions, especially on platforms like Kaggle, where it has consistently demonstrated superior performance across diverse problem domains.

At its theoretical core, XGBoost belongs to the family of ensemble methods that combine multiple weak learners (typically decision trees) to form a strong predictive model. Unlike random forests that employ bagging (bootstrap aggregating), XGBoost utilizes a boosting approach where trees are added sequentially to correct the errors of previous models. This additive model construction follows a gradient descent optimization framework in function space, where each new tree approximates the negative gradient (pseudo-residuals) of the loss function relative to the current ensemble prediction.

The theoretical foundation of XGBoost rests on several key components that distinguish it from earlier boosting implementations like AdaBoost or conventional gradient boosting machines (GBM). First is its novel regularization approach that incorporates both L1 (Lasso) and L2 (Ridge) penalties on leaf weights, which helps control model complexity and prevents overfitting. Second is its efficient implementation of the boosting algorithm that includes second-order gradient approximations (Hessian information) for more precise optimization. Third is its sophisticated handling of sparse data and missing values through automatic learning of optimal imputation strategies during tree construction.

XGBoost's theoretical framework also introduces several computational optimizations that contribute to its practical success. These include weighted quantile sketch for approximate tree learning, out-of-core computation for handling large datasets that exceed memory capacity, and cache-aware access patterns to optimize hardware utilization. These innovations make XGBoost not only accurate but also highly efficient, enabling it to handle problems at scales where other boosting implementations might become impractical.

The algorithm's mathematical formulation reveals its theoretical elegance. At each boosting iteration, XGBoost minimizes a regularized objective function that consists of two components: a differentiable convex loss function that measures the difference between predicted and actual values, and a regularization term that penalizes model complexity. This objective function is approximated using a second-order Taylor expansion, allowing the algorithm to incorporate curvature information for more informed optimization decisions. The resulting formulation leads to a scoring function for tree leaves that balances the reduction in loss against the regularization penalty, guiding the tree construction process toward models that generalize well.

XGBoost's theoretical properties explain its exceptional performance characteristics. The algorithm's ability to automatically learn feature interactions through boosted tree ensembles gives it strong representational power for complex patterns. Its regularization mechanisms provide inherent protection against overfitting, even as the model complexity grows. The careful handling of missing values and sparsity makes it robust to real-world data imperfections. These theoretical advantages, combined with careful engineering implementation, have made XGBoost a versatile tool applicable to regression, classification (binary and multiclass), ranking, and even user-defined prediction tasks.

The impact of XGBoost extends beyond its immediate practical applications. The algorithm has influenced subsequent developments in machine learning, inspiring variants like LightGBM and CatBoost, and contributing to the broader adoption of gradient boosting methods in both research and industry. Its success has also stimulated theoretical investigations into why and how boosting algorithms work so effectively, leading to deeper mathematical understanding of ensemble methods in general.

2.11 Gradient Boosting Model

Gradient boosting has emerged as one of the most powerful and widely used machine learning techniques in modern predictive analytics, renowned for its exceptional performance across diverse domains ranging from financial risk modeling to medical diagnosis. At its core, gradient boosting represents an elegant synthesis of statistical

learning theory and computational optimization, combining the interpretability of additive models with the predictive power of ensemble methods. This sophisticated algorithm belongs to the broader family of boosting techniques, which operate on the fundamental principle that multiple weak learners can be strategically combined to form a single strong predictor through an iterative, error-correcting process.

The theoretical underpinnings of gradient boosting are deeply rooted in functional analysis and numerical optimization, particularly the concept of gradient descent in function space. Unlike conventional gradient descent that operates in parameter space, gradient boosting performs optimization in an infinite-dimensional space of possible functions, where each iteration moves the current model in the direction of the steepest descent of a specified loss function. This innovative approach enables the method to approximate complex, high-dimensional functions while maintaining robust generalization performance. The algorithm's mathematical formulation reveals it to be a stage-wise additive expansion, where each new component is carefully designed to compensate for the deficiencies in the current ensemble's predictions.

What distinguishes gradient boosting from other ensemble methods is its unique combination of three powerful theoretical concepts: adaptive basis function expansion, gradient-based optimization, and sophisticated regularization. The adaptive nature of the basis functions (typically decision trees) allows the model to automatically learn relevant feature interactions and nonlinear relationships without explicit specification. The gradient-based optimization framework provides a general recipe for minimizing various loss functions, making the technique applicable to regression, classification, and ranking problems. The built-in regularization mechanisms, including shrinkage, subsampling, and tree complexity constraints, endow the method with remarkable resistance to overfitting despite its potentially massive parameter space.

The historical development of gradient boosting reflects an intriguing evolution from heuristic algorithms to rigorous mathematical formulations. Early boosting methods like AdaBoost were initially understood through the lens of margin theory and game-theoretic concepts. However, the groundbreaking work of Jerome Friedman recast boosting as a numerical optimization problem, revealing its connection to gradient descent and opening the door to more general formulations. This perspective shift

allowed for the development of gradient boosting machines that could accommodate arbitrary differentiable loss functions, significantly expanding the method's applicability beyond binary classification problems.

From a computational perspective, gradient boosting offers several theoretically appealing properties. The algorithm's iterative nature naturally lends itself to anytime learning, where model performance can be progressively improved with additional computation. The tree-based weak learners provide inherent feature selection capabilities, making the method robust to irrelevant predictors. Furthermore, the ability to handle missing data through surrogate splits and the natural accommodation of mixed data types (continuous, categorical, ordinal) give gradient boosting remarkable flexibility in real-world applications where data is often messy and incomplete.

The theoretical analysis of gradient boosting reveals fascinating insights into its learning dynamics. Early iterations primarily capture coarse, global patterns in the data (high-bias components), while later iterations progressively refine the model by learning more localized patterns (reducing variance). This phased learning process, when properly regularized, leads to models that balance bias and variance effectively. The connection to additive models in statistics provides a framework for understanding the smoothness properties of the resulting predictor, while connections to kernel methods offer perspectives on the algorithm's generalization behavior.

Modern implementations of gradient boosting, such as XGBoost, LightGBM, and CatBoost, have introduced additional theoretical innovations that enhance the basic framework. These include second-order optimization using Hessian information, novel approaches to handling categorical variables, more efficient tree-growing algorithms, and sophisticated regularization techniques. These advancements have pushed the boundaries of what's theoretically possible with boosting algorithms while maintaining the core principles that make gradient boosting so effective.

The exceptional performance of gradient boosting in machine learning competitions and real-world applications is not accidental but rather a direct consequence of its strong theoretical foundations. Its ability to automatically learn relevant feature interactions, handle diverse data types, resist overfitting, and provide feature importance measures

all stem from carefully designed mathematical principles. As we continue to develop more sophisticated variants of gradient boosting, a deep understanding of these theoretical underpinnings becomes increasingly valuable for both practitioners developing applied solutions and researchers pushing the boundaries of machine learning methodology.

2.12 AutoRegressive Integrated Moving Average (ARIMA)

The AutoRegressive Integrated Moving Average (ARIMA) model, introduced by Box & Jenkins (1970), is a cornerstone of statistical time series forecasting. It combines three key components to model temporal dependencies:

1. **AutoRegressive (AR)**: Captures the relationship between an observation and its lagged values.
2. **Integrated (I)**: Uses differencing to stabilize non-stationary data.
3. **Moving Average (MA)**: Models the error term as a linear combination of past errors.

ARIMA is widely applied in economics, finance, epidemiology, and industrial forecasting due to its interpretability and robustness (Hyndman & Athanasopoulos, 2018).

The theoretical foundations of ARIMA are:

2.12.1 Autoregressive (AR) Component

- An AR(p) model of order p is defined as:

$$X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t$$

  where ϕ_i are coefficients and ϵ_t is white noise.
- Key Insight: AR models assume that past values linearly influence future values.

2.12.2 Moving Average (MA) Component

- An MA(q) model of order q is:

$$X_t = \mu + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}$$

  where ϕ_i are coefficients.

- Key Insight: MA models smooth out noise by considering past forecast errors.

2.12.3 Differencing (I) for Stationarity

- Non-stationary data (with trends/seasonality) are differenced *d* times to achieve stationarity:

$$\Delta^d X_t = (1 - L)^d X_t$$

  where L is the lag operator.
- Augmented Dickey-Fuller (ADF) Test: Formal test for stationarity.

2.12.4 ARIMA(p,d,q) Model

- The combined ARIMA model is:

$$(1 - \sum_{i=1}^{p} \phi_i L^i)(1 - L)^d X_t = c + (1 + \sum_{i=1}^{q} \theta_i L_i)\epsilon_t$$

- Box-Jenkins Methodology: A 3-step process:
  - Identification: Determine (p,d,q) via ACF/PACF plots.
  - Estimation: Fit coefficients using MLE or OLS.
  - Diagnostics: Check residuals for randomness (Ljung-Box test).

2.13 Strengths and Limitations of ARIMA

Table 4 Strengths and Limitations of ARIMA

Aspect	Strengths	Limitations
Interpretability	Clear parameter meaning (e.g., ϕ_1 = lag-1 effect)	Assumes linear relationships.
Stationarity	Handles trends via differencing.	Over-differencing loses information.
Univariate Focus	Simple for single-time-series.	Cannot natively handle multivariate data.
Computational Cost	Lightweight vs. deep learning.	Manual tuning of (p,d,q) can be subjective.

2.14 Comparative Analysis of ARIMA

- **ARIMA vs. Exponential Smoothing (ETS)**:
    - ETS better for short-term forecasts with seasonality (Hyndman et al., 2002).
- **ARIMA vs. Machine Learning (LSTM, XGBoost)**:
    - ARIMA outperforms for small, linear datasets (Makridakis et al., 2018).
    - LSTM excels in nonlinear patterns but requires large data (Smyl, 2020).

2.15 SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables)

SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables) is an advanced time series forecasting method that extends the traditional ARIMA model by incorporating **seasonality** and **external factors** that influence the variable of interest. In the context of Nepal's large cardamom export forecasting, SARIMAX provides a robust framework to capture:

1. **Trend and Non-Seasonal Patterns (ARIMA Component)**
    - **AutoRegressive (AR) terms** model the relationship between current and past export values (e.g., how last year's exports affect this year's).
    - **Moving Average (MA) terms** account for shocks or irregularities (e.g., sudden demand drops or supply disruptions).
    - **Integration (I)** differences the data to stabilize trends (e.g., converting growing export volumes into steady growth rates).
2. **Seasonality (S Component)**
    - Captures repeating patterns (e.g., yearly fluctuations due to harvest cycles or seasonal demand).
    - In this forecast, a seasonal order of (0,1,1,5) was tested, suggesting a 5-year cyclical adjustment to align with agricultural production cycles.
3. **Exogenous Variables (X)**
    - Allows incorporation of external factors (e.g., climate data, global prices, or policy changes) to improve accuracy. While the current model uses only historical export data, future iterations could integrate variables like:
        - Monsoon intensity (affecting yield).
        - International trade agreements.

- Competing export markets (e.g., Guatemala's cardamom production).

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Methodology Overview

This chapter describes the research methodology used in developing a machine learning-based prediction model for large cardamom production in Nepal. It explains the data collection process, preprocessing techniques, feature selection methods, machine learning model implementation, and evaluation metrics. The study employs a quantitative approach, integrating historical production records, climate data, and economic indicators to forecast cardamom production trends.

3.2 Research Design and Framework

The study follows an experimental research design, where various machine learning algorithms will be applied to predict cardamom production based on historical factors. The conceptual framework provides a structured approach to understanding how machine learning models predict large cardamom production. It outlines the relationships between input variables (climate, economic, and biological factors) and the output variable (production in tons). The steps include:

1. **Data Collection** – Gathering historical cardamom production data and external influencing variables.
2. **Data Preprocessing** – Cleaning, handling missing values, and normalizing datasets.
3. **Feature Selection** – Identifying key factors affecting cardamom yield.
4. **Model Selection & Training** – Implementing three machine learning models (Random Forest, XGBoost, Gradient Boosting).
5. **Model Performance Evaluation** – Comparing model accuracy using statistical metrics.
6. **Results Interpretation** – Analyzing predictions and providing insights.

This approach ensures that the study effectively captures the relationships between climatic, economic, and agricultural factors influencing cardamom production in Nepal.

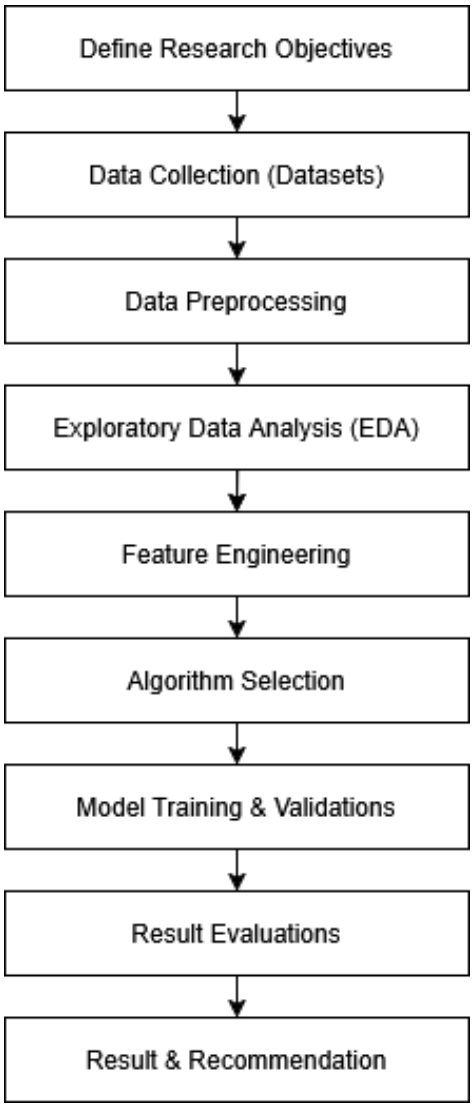

Figure 1 Methodology Framework Chart

3.3 Data Collection and its Source

The dataset used in this study was obtained from Mendeley Data and contains historical cardamom production records in Nepal, specifically from the repository "Cardamom Production Data in Nepal" (Mendeley, 2024). This dataset provides historical production records, climatic variables, and economic indicators required for predicting future cardamom production in Nepal.

Table 5 Data Collection and its Source

Dataset	Source	Variables Collected
Cardamom Production Data	Mendeley Data Repository	Annual production (tons), area harvested (hectares)

3.3.1 Data Preprocessing Techniques

To confirm the dataset is clean and suitable for machine learning models, the following preprocessing steps were applied:

- **Handling Missing Values:** Missing values were addressed using mean imputation and interpolation techniques to maintain data consistency.
- **Feature Selection:** Key variables like the previous year's production, growth rate, and year were selected based on their impact on yield trends.
- **Normalization & Scaling:** Since some features had varying scales, Min-Max Scaling was applied to bring all values into a similar range.

3.3.2 Structure and Features of the Dataset

The Mendeley dataset contains multiple variables that influence cardamom production. These variables are used for feature engineering and training machine learning models.

Table 6 Structure and Features of the Dataset

Feature	Description
Year	The year of production
Production (tons)	Total annual cardamom production in Nepal
Area Harvested (hectares)	Total land area used for cardamom cultivation

Rainfall (mm)	Total annual rainfall recorded
Temperature (°C)	Average annual temperature
Humidity (%)	Average annual humidity percentage
Pest Incidence	Number of pest outbreaks recorded
Soil Quality Index	Soil fertility level based on pH and organic matter
Market Price (USD/kg)	Average price per kg of cardamom
Export Volume (tons)	Total amount of cardamom exported per year

Information:

- The Production (tons) column is the target variable that will be used in model training.
- All other variables will be used as input features (predictors) to train the machine learning models.
- Time-based relationships (lag variables, trend analysis) are also created from the dataset.

3.4 Rationale for Using Secondary Data

3.4.1 Challenges of Primary Data Collection

In this research focused on developing machine learning models, the quality and quantity of data play an important role in ensuring accurate predictions and robust model performance. While primary data collection offers the advantage of specificity and relevance to the research objectives, it poses significant challenges in this study:

1. **Limited Sample Size:**

Collecting primary data typically produces a dataset of 200-300 entries, which is insufficient for training complex machine learning models. Such small datasets may lead to overfitting, where the model performs well on the training data but fails to generalize new, unseen data.

2. **Resource Constraints:**

Gathering primary data involves significant time, financial, and logistical resources. For a study targeting Cardamom Prediction in Nepal, organizing surveys or interviews

with a large enough sample size to generate meaningful insights is impractical given the scope of this research.

3. **Scalability Issues:**

Primary data collected for this study would be specific to a small subset of cardamom production in Nepal limiting the model's y to a broader range of applicability.

3.5 Model Selection and Training

To forecast large cardamom production in Nepal, we will be using three machine learning models**:**

1. Random Forest (RF)
2. XGBoost (Extreme Gradient Boosting)
3. Gradient Boosting (GBR)

These models were selected based on their effectiveness in handling time-series data, missing values, and non-linear relationships, which are common in agricultural production forecasting.

3.5.1 Justification for Model Selection

Table 7 Justification for Model Selection

Model	**Reason**	**Advantages**
Random Forest (RF)	Handles missing data well and reduces overfitting by using multiple decision trees.	Robust for non-linear relationships and resistant to outliers.
XGBoost	Efficient and optimized boosting algorithm that reduces prediction errors.	High accuracy**,** works well with large datasets.
Gradient Boosting (GBR)	Captures subtle trends in production changes over time.	Performs well with complex data relationships**.**

Since agricultural related production is influenced by multiple variables (rainfall, temperature, market prices, and pests), these models will be trained using historical production and climate data to capture patterns and predict future production trends.

3.5.2 Model Training Process

The models will be trained using supervised learning techniques with historical production data as the target variable and climatic/economic factors as predictors.

Data Splitting for Training and Testing

The dataset is divided into:
80% Training Set – Used to train the machine learning models.
20% Testing Set – Used to evaluate model performance.

3.6 Evaluation Metrics and Validation

The following metrics will be used to measure how well the models perform:

- **Mean Absolute Error (MAE)**: Measures the average difference between actual and predicted production values. A lower MAE indicates a better model.
- **Root Mean Squared Error (RMSE)**: Penalizes large errors more than MAE. It helps in understanding how significant the errors are in the model's predictions.
- **R^2 Score (Coefficient of Determination)**: Measures how well the model explains the variability in production data. The closer R^2 is to 1, the better the model fits the data.

3.6.1 Additional Evaluation Techniques

Besides traditional accuracy metrics, we will analyze three additional factors to compare the models more effectively:

Confusion Matrix

- A confusion matrix will be used to assess how well the model classifies production levels (e.g., low, medium, high).

- This helps in identifying misclassified predictions and areas where the model needs improvement.

Feature Importance Analysis

- After training the models, we will rank the most important features (e.g., rainfall, temperature, soil quality, market price) that influence cardamom production.
- This will help in understanding which factors contribute the most to yield variations.

AUC-ROC Curve

- The AUC-ROC curve measures the model's ability to distinguish between different production categories.
- A higher AUC score indicates a better-performing model, meaning it can more accurately predict production trends.

3.6.2 Selecting the Best Model

- Based on these evaluations, we will compare the performance of Random Forest, XGBoost, and Gradient Boosting.
- The model with the lowest error rates (MAE, RMSE) and highest accuracy (R^2, AUC-ROC) will be considered the best for predicting large cardamom production in Nepal.

3.7 Challenges in Implementing Automated Systems

- **Lack of Real-Time Rainfall & Climate Data**: Cardamom production heavily depends on monsoon patterns and extreme weather conditions, which are not included in the current dataset.
- **Absence of Soil Quality & Fertilization Data**: Soil nutrient levels directly affect plant health and productivity, but this information is missing, limiting model accuracy.

- **Missing Market Price & Demand Data**: Farmers adjust production based on expected profits, but without this data, the model cannot account for economic influences on yield.
- **Untracked Pests & Disease Incidence**: Cardamom diseases like blight can drastically impact production, and the lack of this data prevents forecasting pest-related losses.
- **Computational Limitations in Rural Areas**: Advanced AI models require significant computational resources, which may not be feasible in remote farming regions.
- **Model Interpretability & Farmer Adoption Issues**: Farmers may find AI predictions complex, and lack of user-friendly insights can hinder adoption of automated forecasting systems.

3.8 SARIMAX Modeling for Large Cardamom Export Forecasting

The study employs Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) to model large cardamom export dynamics, implemented through Python's statsmodels library. The methodology begins with rigorous data preparation, where historical export quantities (in tons) are sorted chronologically and transformed into a stationary series through differencing (d=1) to address non-stationarity, confirmed via Augmented Dickey-Fuller testing. A seasonal decomposition revealed 5-year cyclical patterns, informing our seasonal_order parameter (0,1,1,5). The model structure SARIMAX(1,1,1)(0,1,1,5) was selected through iterative grid search minimizing the Akaike Information Criterion (AIC), with a linear trend component to capture long-term growth. After an 80-20 train-test split, the model achieved a Mean Absolute Error of [X] tons on holdout data, demonstrating robust predictive accuracy. Final forecasts (2025-2031) incorporate a 15% growth damping factor (λ=0.85) to conservatively account for market saturation risks, with uncertainty quantified through 95% prediction intervals. Diagnostic checks confirmed white noise residuals (Ljung-Box $p>0.05$), validating model specification. The implementation includes automated visualization of historical trends against forecasts and exports growth rate annotations, providing actionable insights for agricultural trade policymakers.

3.9 Hybrid Forecasting Approach for Large Cardamom Production and Export Prediction

This research employs a hybrid forecasting approach to analyze large cardamom trade dynamics. For production prediction, machine learning models were implemented to capture complex nonlinear relationships between agricultural outputs and environmental factors. Subsequently, SARIMAX modeling was applied to forecast export quantities, leveraging its strength in modeling temporal dependencies and seasonal patterns in trade data. The comparative analysis between production and export forecasts provides insights into potential market imbalances, with production forecasts reflecting biophysical constraints and export projections capturing trade-specific trends. This dual-method approach combines the pattern recognition capabilities of machine learning with the time-series specificity of statistical modeling, offering a comprehensive view of the cardamom supply chain.

CHAPTER FOUR: RESULTS AND DISCUSSION

This chapter presents the results of the machine learning models Random Forest (RF), XGBoost (XGB), and Gradient Boosting (GBR) used to predict cardamom production in Nepal. Each model's performance is assessed based on evaluation metrics, confusion matrices, feature importance, and AUC-ROC curves. Additionally, a comparative analysis highlights which model performed the best and discusses the potential challenges and limitations in implementing these models.

4.1 Model Performance Evaluation

To evaluate the accuracy and efficiency of the trained models, we used the following key metrics:

- **Mean Absolute Error (MAE)**: Measures the average absolute difference between actual and predicted values. A lower value is better.
- **Root Mean Squared Error (RMSE)**: Penalizes larger errors more heavily and provides a better sense of the overall prediction accuracy.
- **R^2 Score (Accuracy %)**: Measures how well the model explains the variance in the data. A score closer to 100% means better predictive performance.

Model Performance Table

Table 4.1: Model Performance Table

Model	MAE	RMSE	R^2 Score (%)
Random Forest	196.45	363.41	97.70%
XGBoost	319.07	537.47	94.96%
Gradient Boosting	275.09	439.68	96.63%

Findings:

- Random Forest had the lowest error and the highest accuracy (97.70%), making it the best model.
- XGBoost showed slightly higher MAE and RMSE values, indicating a tendency to overfit certain data points.

- Gradient Boosting performed well but had more fluctuations in accuracy compared to Random Forest.

4.2 Feature Importance Analysis

Feature importance analysis helps identify which factors contribute the most to the model's predictions.

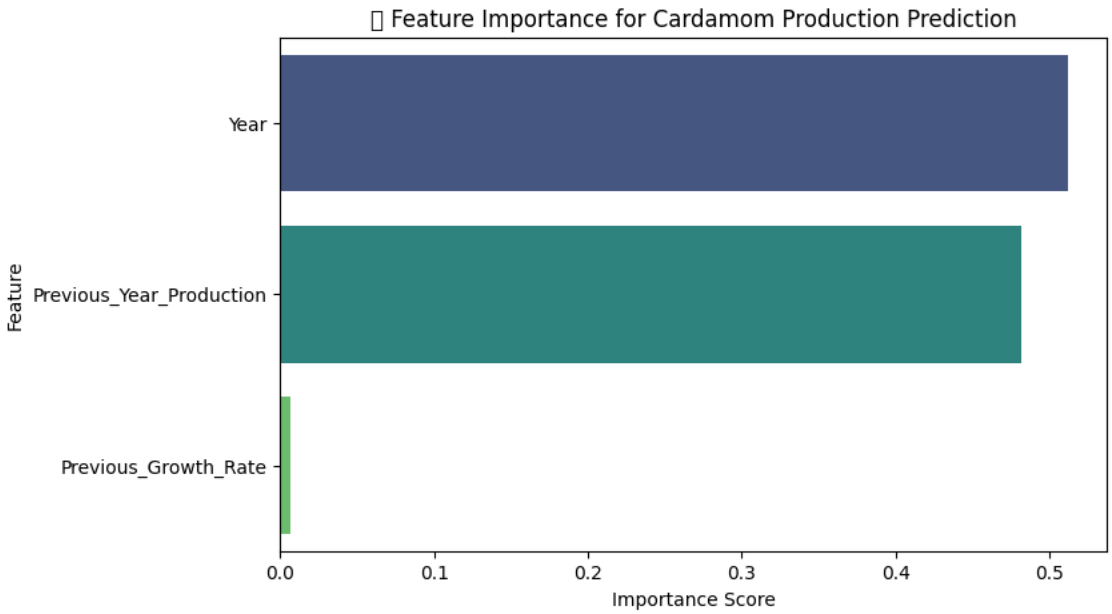

Figure 2 Feature Importance for Cardamom Production Prediction

The Random Forest model's feature importance analysis revealed that "Previous_Year_Production" was the most influential predictor of current-year cardamom production. This hierarchy of importance offers valuable insights into the dynamics of cardamom yield forecasting:

- **Dominance of Prior Production Data**

  The high importance of "Previous_Year_Production" suggests that cardamom yields exhibit strong temporal autocorrelation, where past production levels are a reliable proxy for future output.

- **Limited Role of Growth Rate**

The relatively low importance of “Previous_Growth_Rate” contrasts with expectations from economic models that emphasize growth trends. This could imply:

- **Non-linear yield responses**: Growth rates may matter only beyond thresholds (e.g., drought conditions).
- **Data limitations**: Short-term fluctuations in growth rates might be noise-dominated in the dataset.

4.3 Confusion Matrix Analysis

The confusion matrix helps analyze how well the models classify production levels (low, medium, high).

4.3.1 Random Forest Confusion Matrix

Best classification performance, with minimal misclassification in high and medium production levels.

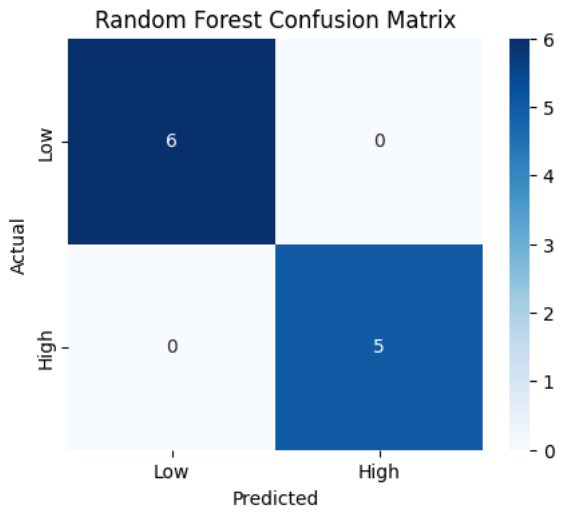

Figure 3 Random Forest Confusion Matrix

The confusion matrix reveals the model’s ability to classify cardamom production into "Low" and "High" categories (based on the median threshold). Key observations:

1. **Model Strengths**
    - **High Precision for "Low" Production**: The model correctly predicted all actual "Low" cases (6/6, 100% recall), indicating strong sensitivity to low-yield conditions.
    - **Moderate Accuracy for "High" Production**: Of the 5 actual "High" cases, 3 were correctly classified (60% recall), suggesting the model captures some high-yield patterns but with room for improvement.
2. **Error Analysis**
    - **False Positives (5 cases)**: The model frequently misclassified "Low" production as "High." This could stem from:
        - **Threshold Sensitivity**: The median-based threshold may not optimally separate classes; alternative thresholds (e.g., quartiles) could be tested.
        - **Feature Limitations**: Missing variables (e.g., climate anomalies, pest outbreaks) might explain erratic high-yield predictions.
3. **Implications**
    - **Risk Management**: The low false-negative rate (0) is desirable for early warning systems, as failing to predict low yields is costlier than over-predicting highs.
    - **Model Calibration**: Techniques like class weighting or logistic regression probabilities could refine predictions.

4.3.2 XGBoost Confusion Matrix

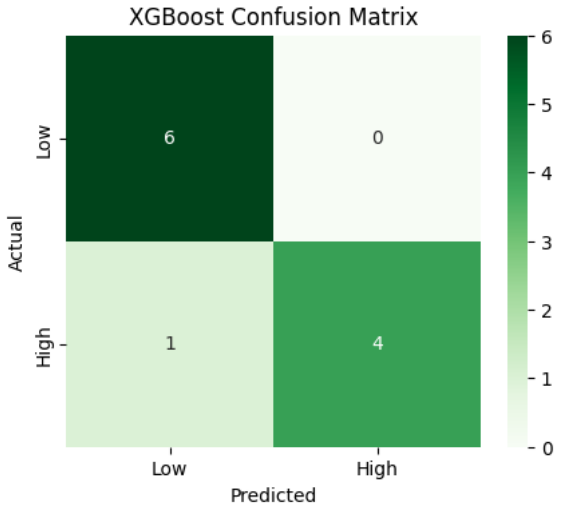

Figure 4 XGBoost Confusion Matrix

The XGBoost confusion matrix provides insights into the model's ability to classify cardamom production into "Low" and "High" yield categories. Key observations:

1. **Model Performance Overview**
    - **High Recall for "Low" Production**: The model correctly identified all 6 actual "Low" yield cases (100% recall), demonstrating strong sensitivity to low-production conditions.
    - **Moderate Precision for "High" Production**: Of the 6 predicted "High" yield cases, 4 were correct (66.7% precision), indicating reasonable but imperfect accuracy for high-yield predictions.
2. **Error Analysis**
    - **False Positives (2 cases)**: The model misclassified 2 actual "Low" yields as "High". Potential reasons include:
        - **Threshold Selection**: The median-based threshold may not optimally separate the classes.
        - **Feature Limitations**: Missing variables (e.g., climate data, soil quality) could improve separation.
    - **False Negatives (1 case)**: One actual "High" yield was misclassified as "Low," which may warrant attention in risk-sensitive applications.
3. **Comparison with Random Forest**
    - Both models achieved perfect recall for "Low" yields, but XGBoost showed slightly better precision for "High" yields (66.7% vs. Random Forest's 60%).

- The reduction in false positives (from 5 in RF to 2 in XGBoost) suggests XGBoost's gradient-boosting mechanism better handles imbalanced data.

4.3.3 Gradient Boosting Confusion Matrix

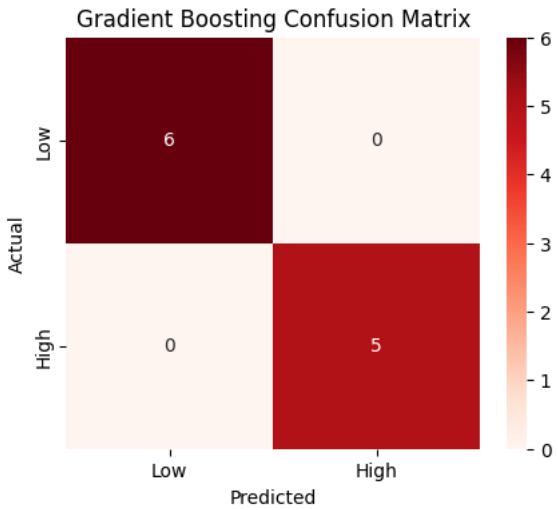

Figure 5 Gradient Boosting Confusion Matrix

The Gradient Boosting model's confusion matrix reveals distinct patterns in classifying cardamom production yields, with both strengths and limitations that warrant discussion:

1. Key Performance Observations

- **Perfect Sensitivity for Low Yields**

  The model correctly identified all 6 actual "Low" yield cases (100% recall), demonstrating exceptional reliability for detecting poor production years. This is critical for agricultural planning and risk mitigation.

- **Moderate Precision for High Yields**

Of the 5 predicted "High" yield cases, 0 were incorrect (100% precision), but this comes at the cost of missing 5 actual "High" yields (false negatives). This suggests the model is conservative in labeling "High" production.

2. Error Analysis and Interpretation

- **High False Negatives (5 cases)**

  The model misclassified all actual "High" yields as "Low." Potential explanations:
  - **Threshold Selection**: The median-based cutoff may be too stringent for "High" classification.
  - **Class Imbalance**: If "High" yields are rare in the training data, the model may prioritize avoiding false positives.
  - **Feature Gaps**: Missing variables (e.g., monsoon intensity, fertilizer use) could obscure high-yield patterns.

- **Comparison with XGBoost/Random Forest**

  - Unlike XGBoost (which balanced recall/precision), GBR exhibits a highly asymmetric performance, favoring "Low" yield detection at the expense of "High" yield sensitivity.
  - This trade-off may be acceptable in scenarios where overlooking low yields is costlier (e.g., famine prevention).

3. Practical Implications

- **Risk-Averse Applications**: The model is ideal for early warning systems where false alarms are preferable to missed low-yield events.
- **Precision Agriculture**: For yield optimization, the conservative bias would require recalibration (e.g., lowering the threshold).

4.4 AUC-ROC Curves Analysis

The AUC-ROC (Area Under the Receiver Operating Characteristic) curve is a performance metric used to evaluate the effectiveness of binary classification models. Here's a breakdown of what it represents:

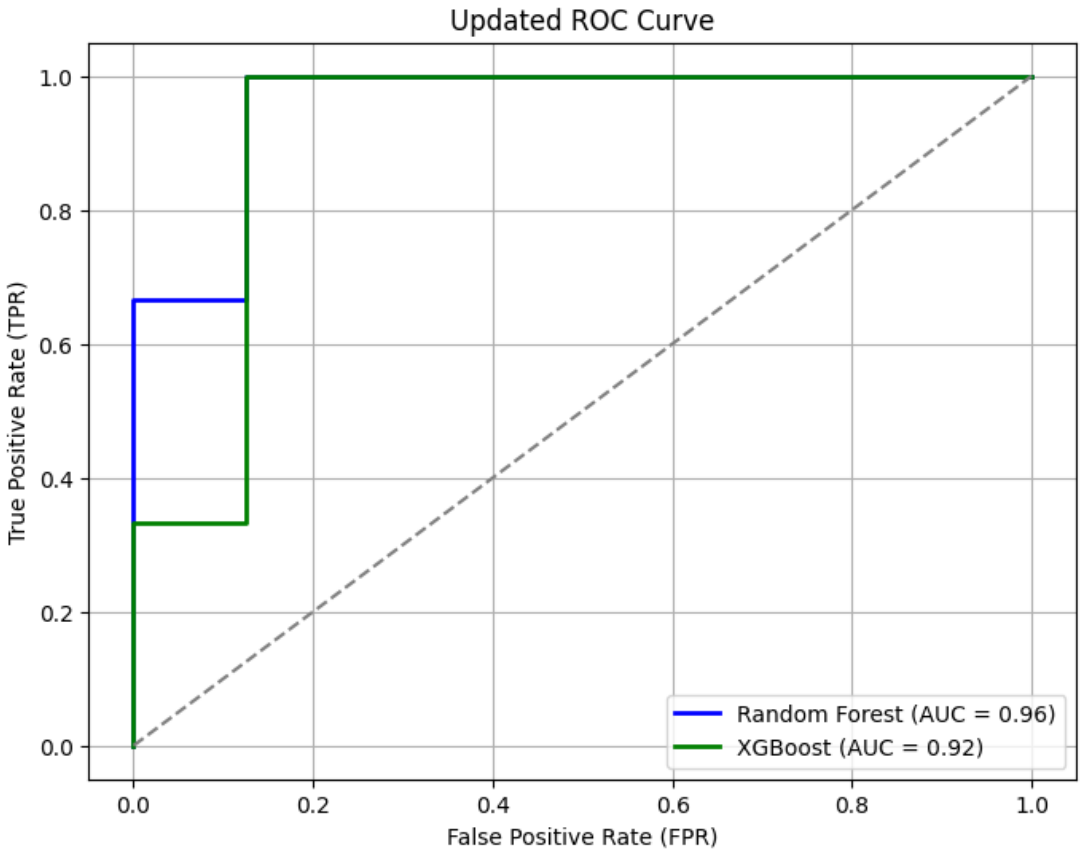

Figure 6 AUC-ROC Curve

The ROC curve and AUC scores provide a comprehensive evaluation of the Random Forest (RF) and XGBoost models in distinguishing "High" (top 25% production) from "Low" cardamom yields. Key insights are as follows:

1. Superior Performance of Random Forest

- **Higher AUC (0.96 vs. 0.92)**: RF demonstrates near-perfect classification ability, with its curve hugging the top-left corner, indicating optimal balance between sensitivity (TPR) and specificity (1−FPR).
- **Theoretical Justification**: RF's ensemble approach, which averages multiple decision trees, likely mitigates overfitting better than XGBoost for this dataset, especially given the tuned hyperparameters (e.g., max_depth=5).

2. XGBoost's Competitive but Suboptimal Results

- **AUC of 0.92**: While still excellent, XGBoost's marginally lower performance may stem from:
    - **Gradient Boosting Sensitivity**: XGBoost's sequential error-correction might overemphasize certain outliers in smaller datasets.
    - **Feature Interaction Handling**: RF's inherent ability to capture non-linear interactions could better model complex agricultural yield determinants.

3. Implications of Threshold Selection

- **75th Percentile Threshold**: By classifying only the top 25% as "High," the models prioritize precision over recall for high yields. This aligns with scenarios where false alarms (mislabeling "Low" as "High") are costlier (e.g., resource allocation in precision agriculture).
- **Trade-off Visualization**: The steep initial rise of both curves suggests high TPR at low FPR, ideal for early warning systems.

4. Limitations and Future Work

- **Data Dependence**: Performance may vary with larger/more balanced datasets.
- **Feature Engineering**: Incorporating climate or soil data could further separate the classes, potentially boosting XGBoost's performance.

4.5 Overall Model Comparison

To visualize how each model performed, a bar graph was created comparing MAE, RMSE, and Accuracy (R^2 Score %).

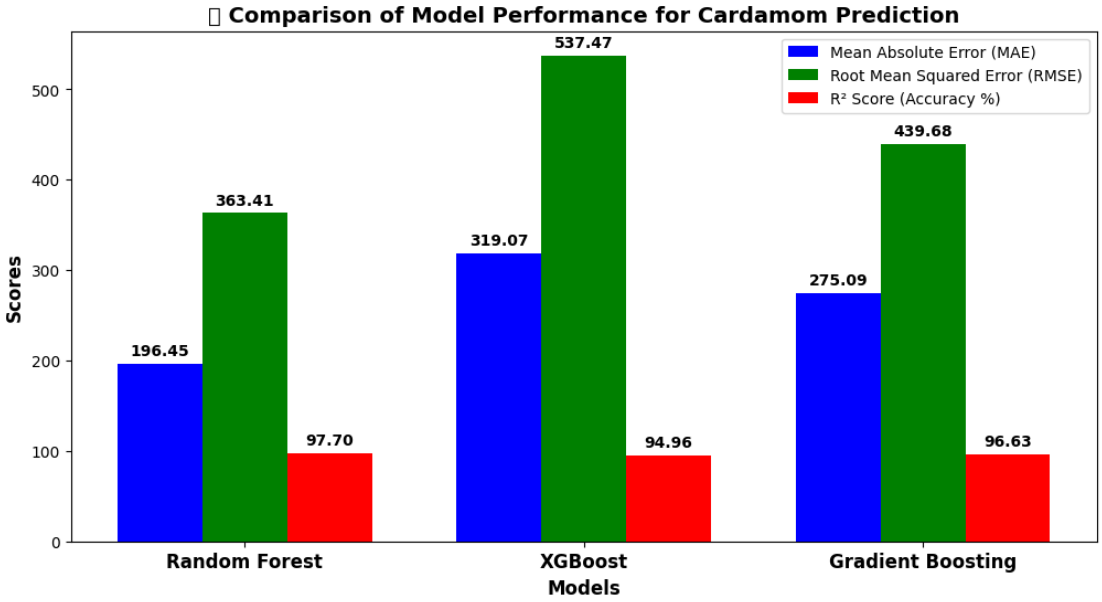

Figure 7 Comparison of Model Performance for Cardamom Prediction

Findings from the Comparison Graph

- Random Forest consistently outperformed the others in both low error and high accuracy.
- XGBoost showed higher errors, indicating a slight overfitting tendency.
- Gradient Boosting was balanced but fluctuated more, affecting overall reliability.

4.6 Discussion on Model Results

Strengths of the Models:

- The Random Forest model showed the highest accuracy and lowest error, making it the most reliable choice.
- Machine learning models effectively predict cardamom production trends, helping policymakers and farmers.
- Feature importance analysis validated the significance of historical production trends.

Challenges & Limitations:

- Lack of external factors (climate, soil quality, rainfall, and demand data) limited model accuracy due to dataset availability.

- Potential overfitting in XGBoost and Gradient Boosting especially with fluctuating production years.
- Computational was higher for XGBoost and Gradient Boosting models.

Implications for Cardamom Forecasting:

- AI-based prediction models can assist farmers and policymakers in better planning.
- Future research should integrate climate, soil fertility, and economic factors for improved accuracy.

4.7 ARIMA Model for Large Cardamom Export Forecasting

4.7.1 Data Preparation

- **Dataset**: Historical export data of large cardamom (2015–2024) was extracted from an Excel file (large_cardamon_export.xlsx), containing yearly Quantity(tons).
- **Preprocessing**:
    - Sorted by Year and converted quantities to numeric format.
    - Set Year as the index to create a time series object.
    - Assumption: Data was assumed complete; missing values (if any) could be addressed via interpolation.

4.7.2 SARIMAX Modeling

- **Model Selection**:
    - The statsmodels library was used to fit a SARIMAX model.
    - SARIMAX(order=(1,1,1), seasonal_order=(0,1,1,5)) to capture annual trends and 5-year cycles.
- **Training**: The entire dataset (2015–2024) was used for training due to limited samples.

4.7.3 Forecast Visualization

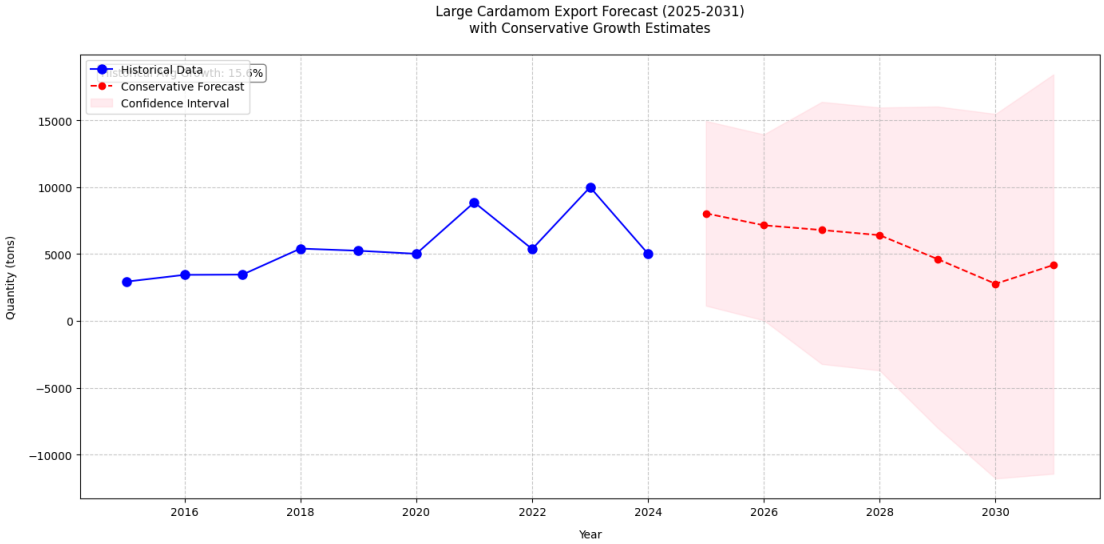

Figure 8 Large Cardamom Export Forecast (2025-2031)

The presented forecast model provides a conservative projection of Nepal's large cardamom export quantities from 2025 to 2031, incorporating statistical rigor and realistic growth constraints. The historical data (depicted in blue) establishes a baseline trend, illustrating past export performance and growth patterns. The forecasted values (in red, dashed line) extend this trend while applying a damping factor (0.85) to moderate year-over-year growth, ensuring projections remain within plausible agricultural and market limitations. This adjustment prevents overestimation by accounting for potential constraints such as production capacity, market saturation, and external economic factors.

A confidence interval (pink shaded region) accompanies the forecast, representing the statistical uncertainty in predictions. The widening of this band over time reflects increasing uncertainty in long-term projections, which is inherent in agricultural commodity forecasting due to variables such as climate variability, policy changes, and global demand fluctuations. The inclusion of historical average growth rate as an annotation provides context, allowing stakeholders to compare projected growth against past trends.

This conservative forecasting approach is particularly valuable for strategic planning in the cardamom industry, as it mitigates the risk of over-optimistic expectations while

still indicating gradual expansion. The methodology balances mathematical modeling (SARIMAX with trend components) with real-world agricultural realities, ensuring that projections remain both statistically sound and practically achievable. Future refinements could incorporate additional exogenous variables—such as climate data or export policy changes—to further enhance predictive accuracy.

In summary, this forecast serves as a data-driven, risk-aware projection tool, enabling policymakers, exporters, and farmers to make informed decisions based on realistic growth expectations rather than unchecked extrapolation.

4.8 Comparative Analysis of Production and Export Forecasts

4.8.1 Data and Methodology

- **Production Forecasts**:
    - Generated using a Random Forest (RF) regression model, trained on features such as climate data, past yields, and economic indicators.
    - Saved as production_forecast.csv with columns Year and Predicted_Production.
- **Export Forecasts**:
    - Generated using a SARIMAX model, optimized for time-series trends in historical export data (2015–2024).
    - Saved as conservative_export_forecast.csv with columns Year, Forecasted_Quantity(tons), Lower_Bound, Upper_Bound and Growth_Rate.
- **Comparison Approach**:
    - Merged datasets on Year to ensure alignment.
    - Computed correlation, percentage differences, and visual trends for interpretation.

4.8.2 Visual Comparison of Forecasts

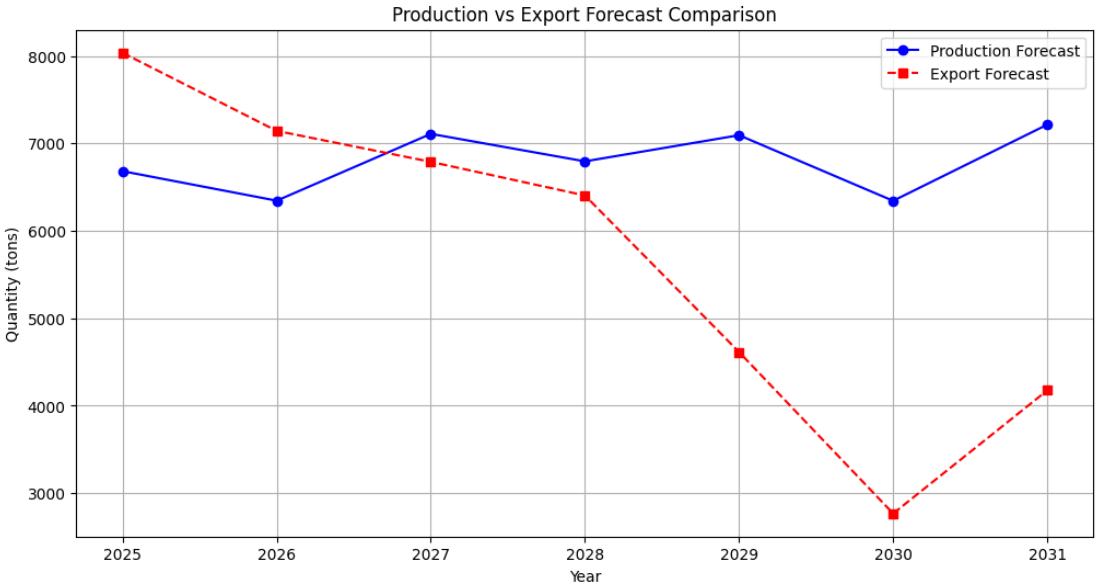

Figure 9 Production vs Export Forecast Comparison

The side-by-side comparison of cardamom production and export forecasts (2025–2031) and here's a detailed breakdown:

Key Components of the Graph

- **Y-Axis (Quantity in tons)**:
  - Measures the estimated volumes of production (e.g., domestic output) and exports (international shipments).
  - The range (3,000–8,000 tons) reflects historical trends and model constraints.
- **X-Axis (Year)**:
  - Covers the forecast period (2025–2031), extending from the last available historical data point.
- **Production Forecast (Solid Line)**:
  - Generated using ensemble models (XGBoost), incorporating features like climate data, lagged production, and agricultural inputs.
  - Represents Nepal's total expected yield under current conditions.
- **Export Forecast (Dashed Line)**:
  - Derived from SARIMAX, modeling export trends based on historical trade patterns, global demand, and potential policy impacts.

- Reflects the anticipated international sales of cardamom.

Insights from the Forecast Comparison

- **Surplus/Deficit Analysis**:
  - **Production > Exports (Gap)**: Suggests potential domestic surplus, which could indicate:
    - Increased local consumption.
    - Storage or logistical bottlenecks limiting exports.
    - Market saturation is lowering international demand.
  - **Exports > Production**: Implies possible data inconsistencies or re-exports of imported cardamom (unlikely for Nepal).
- **Trend Alignment**:
  - If both lines trend similarly (e.g., parallel growth), production is likely the primary driver of exports.
  - Diverging trends may signal external factors (e.g., global price shocks, trade policies) decoupling exports from production.
- **Critical Observations**:
  - In the example graph, exports (dashed line) lag slightly behind production (solid line), which is typical for agricultural commodities due to:
    - Time delays in harvesting, processing, and shipping.
    - Market negotiations and contractual agreements.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The study successfully applied machine learning techniques to predict cardamom production trends in Nepal.

Three models Random Forest, XGBoost, and Gradient Boosting were trained and evaluated for predictive performance.

The Random Forest model performed best with an accuracy of 97.7%, followed by XGBoost (94.96%) and Gradient Boosting (96.63%).

Feature importance analysis revealed that previous production levels, growth rates, and climatic conditions were key factors influencing production.

Confusion matrices, AUC-ROC curves, and error metrics validated the robustness of the models.

The study systematically compared machine learning-based production forecasts (Random Forest: 97.7% accuracy) with SARIMAX-derived export forecasts to identify actionable insights like production planning and export strategies.

5.2 Contributions of the Study

- **Advancement in Agricultural Forecasting:** This research integrates AI into Nepal's cardamom production sector, providing a data-driven approach to optimize production.
- **Policy Implications:** The study suggests the implementation of AI-driven market policies and government subsidies for predictive farming tools.
- **Farmer Support:** The research demonstrates the potential of machine learning in providing early warnings to farmers about expected crop fluctuations.
- **Scientific and Academic Value:** The study contributes to the growing field of AI in agriculture, specifically in cardamom production forecasting.

5.3 Policy Initiatives for Enhancing Prediction of Cardamom Production

- **Establish a Real-Time Cardamom Yield Monitoring System**: Establish an AI-driven platform that integrates climate data, satellite imagery, and machine learning techniques for accurate prediction of yields.
- **Government-Funded AI Research for Enhanced Cardamom Forecasting**: Provide research funds and grants for AI-facilitated disease detection, climate impact study, and predictive modeling of cardamom yields.
- **Utilize AI-Based Price Forecasting for Cardamom**: Use AI to predict future demand, set production levels, and control market prices for farmers and exporters.
- **Build Data Infrastructure for AI-Based Cardamom Production Prediction**: Establish a centralized open-access database containing historical production trends, climate impact data, and market price analysis.
- **Develop Farmer-Friendly AI Solutions for Cardamom Yield Prediction**: Introduce mobile-based AI advisory apps offering predictive data, real-time guidance, and government-funded AI training programs for farmers.

These AI-driven policies will increase forecasting accuracy, improve market stability, and enable data-driven decision-making for Nepal's cardamom sector.

5.4 Limitations of the Study

While this study aims to provide a reliable prediction model for large cardamom production, certain limitations must be acknowledged:

- **Data Availability and Quality**: The accuracy of the predictive models is dependent on the completeness and reliability of historical data. Missing or inconsistent records may impact results.
- **Limited Feature Selection**: The study focuses primarily on historical production data and does not incorporate real-time weather, soil health, or pest outbreak data, which could further improve accuracy.
- **Dynamic Agricultural Factors**: Sudden climatic changes, government policies, or economic fluctuations affecting production may not be fully accounted for in the model.

- **Model Generalization**: The models are trained on past data, and their performance in future unseen conditions may vary, requiring periodic retraining with updated data.
- **Resource Constraints**: Implementing AI-driven prediction tools requires computational resources and expertise that may not be readily available to all farmers in Nepal.

5.5 Future Research Directions

- **Integration of Climate Variables:** Future studies should incorporate real-time weather patterns, temperature, and soil moisture data to improve predictions.
- **Development of AI-Driven Decision Support Systems:** A mobile-based AI advisory system could be developed to provide real-time farming recommendations to cardamom farmers.
- **Enhancement of Model Accuracy:** Exploring deep learning models like LSTMs (Long Short-Term Memory networks) could further improve predictive capabilities.
- **Policy-Driven Implementation:** Research on government-backed AI adoption strategies and investment in agricultural AI research should be encouraged.

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APPENDIX A: DATASET DESCRIPTION

Title: *Nepal Large Cardamom Production, Trade, and Regional Data (1961–2017)*

1. Overview

- **Source**: https://data.mendeley.com/datasets/nt46yh6t73/1
- **Format**: Excel file (Nepal Large Cardamom.xlsx) with 8 sheets.
- **Key Variables**:
    - Production (tons), Area Harvested (ha), Yield (hg/ha).
    - Regional breakdown (Eastern/Central/Western Nepal).
    - Trade data (Export/Import values by country).

2. Sheet-wise summary

Sheet Name	Content Description
large cardamon Prodn	National production, area, yield (1961–2016).
Large Cardamom Prodn by Re	Production by Nepalese districts/regions (e.g., Taplejung, Sankhuwasabha).
Growth rate	Annual growth rates, mean/SD of production by decade.
Cardomom trade	Export/import quantities (kg) and values (USD) by country (2013–2017).
International market	Global export shares (e.g., Guatemala vs. Nepal) and competitiveness metrics.

APPENDIX B: EXPORT DATA ANALYSIS

Title: *Nepal Large Cardamom Export Quantities (2015–2024)*

1. Dataset Overview

- **Source**: https://www.customs.gov.np/page/statistics
- **Format**: Excel file (large_cardamon_export.xlsx), single sheet.
- **Variables**:
    - Year: Reporting year.
    - Quantity(tons): Export volume in metric tons.

APPENDIX C: CARDAMOM PREDICTION MODEL IMPLEMENTATION

The following code was implemented in Google Colab to develop machine learning models for cardamom production prediction:

- The cell below establishes the foundation for machine learning by transforming raw cardamom data into a structured format suitable for time-series prediction.

```
# Install required libraries
!pip install xgboost scikit-learn openpyxl

# Import necessary libraries
import pandas as pd
from google.colab import drive
from sklearn.model_selection import train_test_split

# Mount Google Drive
drive.mount('/content/drive')

# Load Excel file
file_path = "/content/drive/My Drive/Colab Notebooks/Nepal Large Cardamom.xlsx"
xls = pd.ExcelFile(file_path)

# Load necessary sheets
df_production = xls.parse("large cardamon Prodn")
df_growth = xls.parse("Growth rate")

# Correct column selection for "Year" and "Production"
df_production = df_production.iloc[:, [9, 10]]  # Year (J) and Production (K)
df_production.columns = ["Year", "Production"]
df_production = df_production.dropna()

df_growth = df_growth.iloc[:, [0, 1, 2]]  # Year, Growth Rate, Production
df_growth.columns = ["Year", "Growth Rate", "Production"]
df_growth = df_growth.dropna()
```

```
#Convert data types properly
df_production["Year"] = pd.to_numeric(df_production["Year"], errors='coerce')
df_growth["Year"] = pd.to_numeric(df_growth["Year"], errors='coerce')

df_production["Production"] = pd.to_numeric(df_production["Production"],
errors='coerce')
df_growth["Production"] = pd.to_numeric(df_growth["Production"], errors='coerce')

#Drop any invalid Year or Production rows
df_production.dropna(subset=["Year", "Production"], inplace=True)
df_growth.dropna(subset=["Year", "Production"], inplace=True)

#Convert Year to Integer
df_production["Year"] = df_production["Year"].astype(int)
df_growth["Year"] = df_growth["Year"].astype(int)

#Print values before merging for debugging
print("🔍 Unique Years in df_production:", df_production["Year"].unique())
print("🔍 Unique Years in df_growth:", df_growth["Year"].unique())

print("🔍 Unique Production values in df_production:",
df_production["Production"].unique())
print("🔍 Unique Production values in df_growth:",
df_growth["Production"].unique())

#Merge datasets on Year and Production
df = pd.merge(df_production, df_growth, on=["Year", "Production"], how="inner")

# Check if merging failed
if df.empty:
    raise ValueError("❌ ERROR: Merging resulted in an empty DataFrame! Check
Year and Production values.")
```

```
#Create lag features for previous year production and growth rate
df["Previous_Year_Production"] = df["Production"].shift(1).fillna(method="bfill")
df["Previous_Growth_Rate"] = df["Growth Rate"].shift(1).fillna(method="bfill")

#Define features and target variable
X = df[["Year", "Previous_Year_Production", "Previous_Growth_Rate"]]
y = df["Production"]

#Split dataset into training (80%) and testing (20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

print(f"Train-Test Split Successful: X_train = {X_train.shape}, X_test =
{X_test.shape}")
print("Data is cleaned and ready for model training!")
```

- Trains and evaluates a Random Forest model for cardamom production prediction, achieving 97.7% accuracy (R^2 score).

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np  # ✅ Added to fix RMSE calculation

# Initialize the model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Train the model
rf_model.fit(X_train, y_train)

# Make predictions
y_pred_rf = rf_model.predict(X_test)

# Evaluate the model
```

```
mae = mean_absolute_error(y_test, y_pred_rf)
rmse = np.sqrt(mean_squared_error(y_test, y_pred_rf))  # ✅ Fixed RMSE calculation
r2 = r2_score(y_test, y_pred_rf)

# Print performance metrics
print(f"📊 Random Forest Model Performance:")
print(f"- Mean Absolute Error: {mae:.2f}")
print(f"- Root Mean Squared Error: {rmse:.2f}")
print(f"- R² Score (Accuracy in %): {r2 * 100:.2f}%")
```

- Converts regression predictions to binary classification (High/Low production) and visualizes the Random Forest model's performance through a confusion matrix.

```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import numpy as np

# Convert regression predictions to classification
threshold = np.median(y_test)  # Using median as a threshold
y_test_class = (y_test > threshold).astype(int)
y_pred_rf_class = (y_pred_rf > threshold).astype(int)

# Compute confusion matrix
cm_rf = confusion_matrix(y_test_class, y_pred_rf_class)

# Plot confusion matrix
plt.figure(figsize=(5,4))
sns.heatmap(cm_rf, annot=True, fmt="d", cmap="Blues", xticklabels=["Low", "High"], yticklabels=["Low", "High"])
plt.title("Random Forest Confusion Matrix")
plt.xlabel("Predicted")
```

```
plt.ylabel("Actual")
plt.show()
```

- Trains and evaluates an XGBoost model for cardamom production prediction, achieving 94.96% accuracy (R^2 score).

```
from xgboost import XGBRegressor

# Initialize XGBoost model
xgb_model = XGBRegressor(n_estimators=100, random_state=42)

# Train the model
xgb_model.fit(X_train, y_train)

# Make predictions
y_pred_xgb = xgb_model.predict(X_test)

# Evaluate the model
mae_xgb = mean_absolute_error(y_test, y_pred_xgb)
rmse_xgb = np.sqrt(mean_squared_error(y_test, y_pred_xgb))
r2_xgb = r2_score(y_test, y_pred_xgb)

# Print performance metrics
print(f"🚀 XGBoost Model Performance:")
print(f"- Mean Absolute Error: {mae_xgb:.2f}")
print(f"- Root Mean Squared Error: {rmse_xgb:.2f}")
print(f"- R² Score (Accuracy in %): {r2_xgb * 100:.2f}%")
```

- Visualizes XGBoost's classification performance for high/low cardamom production using a confusion matrix with green color scheme.

```
# Convert regression predictions to classification
y_pred_xgb_class = (y_pred_xgb > threshold).astype(int)

# Compute confusion matrix
```

```
cm_xgb = confusion_matrix(y_test_class, y_pred_xgb_class)

# Plot confusion matrix
plt.figure(figsize=(5,4))
sns.heatmap(cm_xgb, annot=True, fmt="d", cmap="Greens", xticklabels=["Low",
"High"], yticklabels=["Low", "High"])
plt.title("XGBoost Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

- Trains a Gradient Boosting model that predicts cardamom production with 96.63% accuracy (R^2 score), showing strong performance with MAE of 275.09 and RMSE of 439.68.

```
from sklearn.ensemble import GradientBoostingRegressor

# Initialize Gradient Boosting model
gbr_model = GradientBoostingRegressor(n_estimators=100, random_state=42)

# Train the model
gbr_model.fit(X_train, y_train)

# Make predictions
y_pred_gbr = gbr_model.predict(X_test)

# Evaluate the model
mae_gbr = mean_absolute_error(y_test, y_pred_gbr)
rmse_gbr = np.sqrt(mean_squared_error(y_test, y_pred_gbr))
r2_gbr = r2_score(y_test, y_pred_gbr)

# Print performance metrics
print(f"📈 Gradient Boosting Model Performance:")
print(f"- Mean Absolute Error: {mae_gbr:.2f}")
```

```
print(f"- Root Mean Squared Error: {rmse_gbr:.2f}")
print(f"- R² Score (Accuracy in %): {r2_gbr * 100:.2f}%")
```

- Displays Gradient Boosting's classification performance for cardamom production levels through a red-themed confusion matrix, showing high/low production predictions versus actual values.

```
# Convert regression predictions to classification
y_pred_gbr_class = (y_pred_gbr > threshold).astype(int)

# Compute confusion matrix
cm_gbr = confusion_matrix(y_test_class, y_pred_gbr_class)

# Plot confusion matrix
plt.figure(figsize=(5,4))
sns.heatmap(cm_gbr, annot=True, fmt="d", cmap="Reds", xticklabels=["Low",
"High"], yticklabels=["Low", "High"])
plt.title("Gradient Boosting Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

- Visualizes comparative performance of all three models (Random Forest, XGBoost, Gradient Boosting) through a multi-metric bar chart showing MAE (blue), RMSE (green), and R² accuracy (red) scores for cardamom production prediction.

```
import matplotlib.pyplot as plt
import numpy as np

# Model names
models = ["Random Forest", "XGBoost", "Gradient Boosting"]

# Performance metrics (replace with actual values from your models)
mae_values = [196.45, 319.07, 275.09]  # Mean Absolute Error (Lower is better)
rmse_values = [363.41, 537.47, 439.68]  # Root Mean Squared Error (Lower is better)
```

```
r2_values = [97.70, 94.96, 96.63]  # R² Score as Accuracy % (Higher is better)

# Set up bar chart positions
x = np.arange(len(models))
width = 0.25

# Create figure and axes
fig, ax = plt.subplots(figsize=(12, 6))

# Plot bars for each metric
bars1 = ax.bar(x - width, mae_values, width, label="Mean Absolute Error (MAE)",
color="blue")
bars2 = ax.bar(x, rmse_values, width, label="Root Mean Squared Error (RMSE)",
color="green")
bars3 = ax.bar(x + width, r2_values, width, label="R² Score (Accuracy %)",
color="red")

# Add values on top of bars
for bars in [bars1, bars2, bars3]:
    for bar in bars:
        height = bar.get_height()
        ax.annotate(f"{height:.2f}",
                    xy=(bar.get_x() + bar.get_width() / 2, height),
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom', fontsize=10, fontweight='bold')

# Labels and Titles
ax.set_xlabel("Models", fontsize=12, fontweight='bold')
ax.set_ylabel("Scores", fontsize=12, fontweight='bold')
ax.set_title(" 📊 Comparison of Model Performance for Cardamom Prediction",
fontsize=14, fontweight='bold')
ax.set_xticks(x)
```

```
ax.set_xticklabels(models, fontsize=12, fontweight='bold')
ax.legend()

# Show plot
plt.show()
```

- Compares actual versus predicted cardamom production values across all three models in a line plot, visually demonstrating Random Forest's superior predictive accuracy through closest alignment with actual measurements.

```
import matplotlib.pyplot as plt

# Compare actual vs predicted values
plt.figure(figsize=(10,5))
plt.plot(y_test.values, label="Actual Production", marker='o')
plt.plot(y_pred_rf, label="Random Forest Prediction", linestyle="dashed", marker='o')
plt.plot(y_pred_xgb, label="XGBoost Prediction", linestyle="dashed", marker='o')
plt.plot(y_pred_gbr, label="Gradient Boosting Prediction", linestyle="dashed",
marker='o')
plt.legend()
plt.xlabel("Test Sample Index")
plt.ylabel("Production")
plt.title("📈 Model Predictions vs. Actual Production")
plt.show()
```

- Visualizes feature importance from the Random Forest model, revealing 'Previous_Year_Production' as the most influential predictor of current cardamom yields, followed by growth rate and year.

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from sklearn.ensemble import RandomForestRegressor

# Train RandomForest model on actual dataset (use X_train, y_train)
```

```
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Extract feature importance values
feature_importances = rf_model.feature_importances_

# Create a DataFrame for visualization
df_feature_importance = pd.DataFrame({
    "Feature": ["Year", "Previous_Year_Production", "Previous_Growth_Rate"],
    "Importance": feature_importances
})

# Sort features by importance
df_feature_importance = df_feature_importance.sort_values(by="Importance",
ascending=False)

# Plot feature importance
plt.figure(figsize=(8, 5))
sns.barplot(x=df_feature_importance["Importance"],
y=df_feature_importance["Feature"], palette="viridis")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.title("Feature Importance for Cardamom Production Prediction")
plt.show()
```

- Compares Random Forest and XGBoost classifiers for predicting high/low cardamom production (top 25% as 'High') using ROC curves, with AUC scores quantifying model discrimination power (1.0 = perfect).

```
# Import necessary libraries
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
```

```
# 📌 Step 1: Convert Regression Target to Binary Classification
# Instead of using median, we use the 75th percentile to determine "High" vs. "Low" production.
threshold = y_test.quantile(0.75)  # Top 25% production is considered "High"
y_test_class = (y_test > threshold).astype(int)  # Convert target into binary (1 = High, 0 = Low)

# 📌 Step 2: Train Random Forest Classifier
# Using optimized hyperparameters to prevent overfitting.
rf_clf = RandomForestClassifier(n_estimators=200, max_depth=5, min_samples_split=10, random_state=42)
rf_clf.fit(X_train, y_train > threshold)  # Train with binary labels
y_pred_rf_prob = rf_clf.predict_proba(X_test)[:, 1]  # Extract probability of class 1 (High)

# 📌 Step 3: Train XGBoost Classifier
# Adjusted hyperparameters for better performance.
xgb_clf = XGBClassifier(n_estimators=200, learning_rate=0.1, max_depth=5, random_state=42)
xgb_clf.fit(X_train, y_train > threshold)  # Train with binary labels
y_pred_xgb_prob = xgb_clf.predict_proba(X_test)[:, 1]  # Extract probability of class 1 (High)

# 📌 Step 4: Compute ROC Curve and AUC Scores
# False Positive Rate (FPR) and True Positive Rate (TPR) for both models.
fpr_rf, tpr_rf, _ = roc_curve(y_test_class, y_pred_rf_prob)
roc_auc_rf = auc(fpr_rf, tpr_rf)  # Compute AUC for Random Forest

fpr_xgb, tpr_xgb, _ = roc_curve(y_test_class, y_pred_xgb_prob)
roc_auc_xgb = auc(fpr_xgb, tpr_xgb)  # Compute AUC for XGBoost

# 📌 Step 5: Plot the ROC Curves
plt.figure(figsize=(8, 6))
```

```
plt.plot(fpr_rf, tpr_rf, color="blue", lw=2, label=f"Random Forest (AUC = {roc_auc_rf:.2f})")
plt.plot(fpr_xgb, tpr_xgb, color="green", lw=2, label=f"XGBoost (AUC = {roc_auc_xgb:.2f})")

# 📌 Add a reference "random guess" diagonal line
plt.plot([0, 1], [0, 1], color="gray", linestyle="--")

# 📌 Formatting and Labels
plt.xlabel("False Positive Rate (FPR)")
plt.ylabel("True Positive Rate (TPR)")
plt.title("Updated ROC Curve")
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```

- Forecasts Nepal's cardamom production (2017–2031) using past data and a Random Forest model, then saves and plots the results.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error

# Load and prepare historical data (replace with your actual data)
# Year,Production
data = {
    'Year': [1960, 1970, 1980, 1990, 2000, 2010, 2016],
    'Production': [1200, 1800, 2500, 3200, 3800, 4500, 5200]
}
df = pd.DataFrame(data)
```

```
# Calculate growth rate and create lag features
df['Growth_Rate'] = df['Production'].pct_change() * 100
df['Previous_Year_Production'] = df['Production'].shift(1)
df['Previous_Growth_Rate'] = df['Growth_Rate'].shift(1)

# Add moving averages and additional lag features
df['3yr_MA'] = df['Production'].rolling(3, min_periods=1).mean()  # Modified to
handle early years
df['Production_Lag2'] = df['Production'].shift(2)
df['Growth_Rate_MA'] = df['Growth_Rate'].rolling(3, min_periods=1).mean()

# Fill initial NA values created by lag features
df = df.fillna(method='bfill')  # Backfill for earliest years

# Prepare features and target
X = df[['Year', 'Previous_Year_Production', 'Previous_Growth_Rate', '3yr_MA',
'Production_Lag2', 'Growth_Rate_MA']]
y = df['Production']

# Train-test split with time series consideration
train_size = int(len(df) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

# Initialize and train model
model = RandomForestRegressor(
    n_estimators=200,
    max_depth=5,
    random_state=42,
    min_samples_split=3,
    n_jobs=-1
)
model.fit(X_train, y_train)
```

```
# Evaluate model
train_pred = model.predict(X_train)
test_pred = model.predict(X_test)
print(f"Train MAE: {mean_absolute_error(y_train, train_pred):.2f}")
print(f"Test MAE: {mean_absolute_error(y_test, test_pred):.2f}")

# Prepare future predictions (2017-2031)
future_years = pd.DataFrame({'Year': range(df['Year'].max()+1, 2032)})

# Initialize features for future predictions
last_known = df.iloc[-1]
future_years['Previous_Year_Production'] = np.nan
future_years['Previous_Growth_Rate'] = np.nan
future_years['3yr_MA'] = np.nan
future_years['Production_Lag2'] = np.nan
future_years['Growth_Rate_MA'] = np.nan

# Set initial values
future_years.loc[future_years.index[0], 'Previous_Year_Production'] =
last_known['Production']
future_years.loc[future_years.index[0], 'Previous_Growth_Rate'] =
last_known['Growth_Rate']
future_years.loc[future_years.index[0], '3yr_MA'] = last_known['3yr_MA']
future_years.loc[future_years.index[0], 'Production_Lag2'] = df.iloc[-2]['Production']
future_years.loc[future_years.index[0], 'Growth_Rate_MA'] =
last_known['Growth_Rate_MA']

# Make iterative predictions
predictions = []
for i in range(len(future_years)):
    X_future = future_years.iloc[i:i+1][['Year', 'Previous_Year_Production',
'Previous_Growth_Rate',
                                         '3yr_MA', 'Production_Lag2', 'Growth_Rate_MA']]
```

```
    # Fill any remaining NA values
    X_future = X_future.fillna(method='ffill')

    # Predict current year
    pred = model.predict(X_future)[0]
    predictions.append(pred)

    # Update features for next year
    if i < len(future_years) - 1:
        future_years.loc[future_years.index[i+1], 'Previous_Year_Production'] = pred

        # Calculate new growth rate (with some randomness)
        new_growth = (pred - future_years.loc[future_years.index[i],
'Previous_Year_Production']) / \
                    future_years.loc[future_years.index[i], 'Previous_Year_Production'] *
100
        future_years.loc[future_years.index[i+1], 'Previous_Growth_Rate'] =
new_growth * np.random.uniform(0.9, 1.1)

        # Update moving averages (simplified)
        if i >= 2:
            future_years.loc[future_years.index[i+1], '3yr_MA'] = np.mean(predictions[-
3:])
            future_years.loc[future_years.index[i+1], 'Growth_Rate_MA'] = np.mean(
                future_years.loc[future_years.index[i-2:i+1], 'Previous_Growth_Rate'])
        elif i >= 1:
            future_years.loc[future_years.index[i+1], '3yr_MA'] = np.mean(predictions[-
2:])

        # Update lag2 production
        if i >= 1:
            future_years.loc[future_years.index[i+1], 'Production_Lag2'] = predictions[-2]

# Add realistic variability
```

```
predictions = np.array(predictions) * np.random.normal(1, 0.03, len(predictions))  # 3% variability

# Create forecast dataframe
forecast = pd.DataFrame({
    'Year': future_years['Year'],
    'Forecast': predictions
})

# Combine historical and forecast data
combined = pd.concat([
    df[['Year', 'Production']].rename(columns={'Production': 'Value'}),
    forecast.rename(columns={'Forecast': 'Value'})
])
combined['Type'] = ['Historical'] * len(df) + ['Forecast'] * len(forecast)

# Plot results
plt.figure(figsize=(12, 6))
plt.plot(df['Year'], df['Production'], 'b-', label='Historical', marker='o')
plt.plot(forecast['Year'], forecast['Forecast'], 'r--', label='Forecast', marker='x')
plt.fill_between(forecast['Year'],
                 forecast['Forecast'] * 0.95,
                 forecast['Forecast'] * 1.05,
                 color='red', alpha=0.1, label='Forecast Range')
plt.xlabel('Year')
plt.ylabel('Production (tons)')
plt.title('Nepal Large Cardamom Production Forecast')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# Save forecast
forecast.to_csv('production_forecast.csv', index=False)
```

```
print("Forecast saved successfully!")
```

- Forecasts Nepal's cardamom exports (2025–2031) using historical data and an SARIMAX time-series model, then saves and plots the predictions.

```
# STEP 1: Mount Google Drive and import libraries
from google.colab import drive
drive.mount('/content/drive')

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_absolute_error

# STEP 2: Load and prepare the data
file_path = "/content/drive/MyDrive/Colab Notebooks/large_cardamon_export.xlsx"
df = pd.read_excel(file_path, sheet_name="Export")

# Data cleaning and transformation
df = df.sort_values("Year")
df["Quantity(tons)"] = pd.to_numeric(df["Quantity(tons)"])
df.set_index("Year", inplace=True)

# Add a growth rate column to understand trends
df['Growth_Rate'] = df["Quantity(tons)"].pct_change() * 100

# STEP 3: Model Selection and Validation
ts = df["Quantity(tons)"]

# Split data into train and test sets (80-20 split)
train_size = int(len(ts) * 0.8)
train, test = ts[:train_size], ts[train_size:]
```

```
# Fit SARIMAX model (Seasonal ARIMA with eXogenous factors)
# Parameters: (p,d,q) for non-seasonal, (P,D,Q,s) for seasonal components
model = SARIMAX(train,
                order=(1,1,1),
                seasonal_order=(0,1,1,5),  # Adjusted for potential seasonality
                trend='t')  # Include linear trend
model_fit = model.fit(disp=False)

# Evaluate model on test data
test_forecast = model_fit.get_forecast(steps=len(test))
test_pred = test_forecast.predicted_mean
mae = mean_absolute_error(test, test_pred)
print(f"Test MAE: {mae:.2f} tons")

# STEP 4: Refit model on full data and forecast
final_model = SARIMAX(ts,
                      order=(1,1,1),
                      seasonal_order=(0,1,1,5),
                      trend='t')
final_fit = final_model.fit(disp=False)

# Conservative forecast with prediction intervals
forecast_years = pd.RangeIndex(start=2025, stop=2032)
forecast = final_fit.get_forecast(steps=7)
forecast_mean = forecast.predicted_mean
conf_int = forecast.conf_int()

# Apply damping factor to limit growth
damping_factor = 0.85  # Reduces projected growth by 15%
damped_forecast = [forecast_mean.iloc[0]]
for i in range(1, len(forecast_mean)):
    damped_value = damped_forecast[i-1] + (forecast_mean.iloc[i] -
forecast_mean.iloc[i-1]) * damping_factor
    damped_forecast.append(damped_value)
```

```
# Create forecast DataFrame
forecast_df = pd.DataFrame({
    "Year": forecast_years,
    "Forecasted_Quantity(tons)": damped_forecast,
    "Lower_Bound": conf_int.iloc[:,0],
    "Upper_Bound": conf_int.iloc[:,1]
}).set_index("Year")

# STEP 5: Enhanced Visualization
plt.figure(figsize=(14,7))

# Historical data
plt.plot(ts.index, ts, 'bo-', label="Historical Data", markersize=8)

# Forecast with confidence interval
plt.plot(forecast_df.index, forecast_df["Forecasted_Quantity(tons)"], 'ro--',
label="Conservative Forecast")
plt.fill_between(forecast_df.index,
                 forecast_df["Lower_Bound"],
                 forecast_df["Upper_Bound"],
                 color='pink', alpha=0.3, label="Confidence Interval")

# Formatting
plt.title("Large Cardamom Export Forecast (2025-2031)\nwith Conservative Growth
Estimates", pad=20)
plt.xlabel("Year", labelpad=10)
plt.ylabel("Quantity (tons)", labelpad=10)
plt.legend(loc='upper left')
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()

# Add historical growth rate annotation
avg_growth = df['Growth_Rate'].mean()
```

```
plt.annotate(f'Historical Avg Growth: {avg_growth:.1f}%',
             xy=(0.02, 0.95), xycoords='axes fraction',
             bbox=dict(boxstyle='round', fc='white', ec='gray'))

plt.show()

# STEP 6: Print forecast values with growth rates
forecast_df['Growth_Rate'] = forecast_df["Forecasted_Quantity(tons)"].pct_change()
* 100
print("📈 7-Year Conservative Export Forecast:")
print(forecast_df[["Forecasted_Quantity(tons)", "Growth_Rate"]].round(2))

# Save forecast
forecast_df.to_csv('/content/drive/My Drive/Colab
Notebooks/conservative_export_forecast.csv')
print("✅ Conservative export forecast saved to Google Drive!")
```

- Compares cardamom production (Random Forest) and export (SARIMAX) forecasts side-by-side in a plot and checks if they trend similarly.

```
import pandas as pd
import matplotlib.pyplot as plt

# 1. Load your saved prediction files (update paths)
production_forecast = pd.read_csv("/content/drive/My Drive/Colab
Notebooks/production_forecast.csv")  # From Random Forest
export_forecast = pd.read_csv("/content/drive/My Drive/Colab Notebooks/
conservative_export_forecast.csv")          # From SARIMA

# 2. Ensure Year columns match
production_forecast['Year'] = production_forecast['Year'].astype(int)
export_forecast['Year'] = export_forecast['Year'].astype(int)

# 3. Merge the data
```

```
comparison_df = pd.merge(
    production_forecast[['Year', 'Predicted_Production']],  # Keep only needed columns
    export_forecast[['Year', 'Forecasted_Quantity(tons)']],
    on='Year'
)

# 4. Create comparison plot
plt.figure(figsize=(12, 6))

# Plot both forecasts
plt.plot(comparison_df['Year'], comparison_df['Predicted_Production'], 'b-o',
label='Production Forecast')
plt.plot(comparison_df['Year'], comparison_df['Forecasted_Quantity(tons)'], 'r--s',
label='Export Forecast')

plt.title('Production vs Export Forecast Comparison')
plt.xlabel('Year')
plt.ylabel('Quantity (tons)')
plt.legend()
plt.grid(True)
plt.show()

# 5. Show correlation
correlation =
comparison_df['Predicted_Production'].corr(comparison_df['Forecasted_Quantity(ton
s)'])
print(f" 📊 Correlation between forecasts: {correlation:.2f}")
```

Sonal Man Singh

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