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SMART TEA: Churn, Trend, Inventory and Sales Prediction System Using Machine Learning

[1]J.H.P Vithanage, [2]Salwathura S.R, [3]De Silva D.K.T.J.S, [4]Wickramasinghe D.K.G.T.I, [5]Suriya Kumari, [6]Uthpala Samarakoon

[1,2,3,4,5,6]Faculty of Computing, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

Authors E-mail: [1]jithma.hpv@gmail.com, [2]samodhsala88@gmail.com, [3]jayapahandesilva9@gmail.com, [4]thisaruimasha123@gmail.com, [5]suriya.k@sliit.lk, [6]uthpala.s@sliit.lk

***Abstract* - Managing operations at a tea factory requires consistency and planning. This paper presents a complete platform that uses advanced machine learning methods specifically designed for the tea sector. Sales prediction, churn prediction, trend prediction, and smart inventory management are the four essential features of our solution. While using Neural Networks for Churn Prediction offers exact insights into customer churn, utilizing Gradient Boosting for Sales Prediction guarantees accurate revenue estimates. Linear regression models were used for trend prediction and smart inventory management to enable efficient utilization of resources and trend identification. With the help of this integrated system, tea companies can now operate more profitably and sustainably in a market that is always changing. This research acts as a beacon, demonstrating the revolutionary potential of data-driven management as operations in the tea industry evolve.**

Keywords: Sri Lankan Tea Factories, Neural Networks, Gradient Boosting Regressor, Ensemble Methods, Linear regression, Sales Price prediction, Churn prediction, Trend prediction, Inventory management.

I. INTRODUCTION

Success in today's fast-paced and highly competitive corporate environment relies on one's capacity to predict, plan, and optimize a variety of operational variables. Predictive systems are now essential tools for companies in a variety of industries, whether they are managing inventories, sales, maintaining customers, or market trends. These systems make use of modern technologies to deliver priceless forecasts and insights, including machine learning, data analysis, and predictive analytics.

Businesses today use predictive technology to stay ahead in their respective areas, much like the Sri Lankan tea industry did when it adopted predictive analytics to adjust to shifting consumer tastes. These technologies are essential for helping businesses make data-driven decisions, increase operational effectiveness, and maintain their competitiveness.

The importance and uses of sales price prediction systems, churn prediction systems, trend prediction systems, and inventory prediction systems all of which are vital to a company's success in the fast-paced, highly competitive market of todaywill be examined in this introduction.

A) System for Predicting Sales Prices

In the ever-changing business landscape of today, organizations are always looking for new and creative ways to improve their competitiveness. A Sales Price Prediction System is one such instrument that forecasts future product pricing by utilizing cutting-edge technology like machine learning and data analysis. This approach seeks to modify pricing techniques in the same way that Sri Lanka's tea business revolutionized the country's economic landscape. Businesses may establish the best prices, optimize profits, and keep a competitive edge by examining past data and market patterns.

B) System for Predicting Churn

In fiercely competitive markets, customer retention is critical. Businesses need a churn prediction system, especially in markets where there are many options. This technology uses machine learning and data mining techniques to identify clients who are at risk of leaving, much like the tea business uses predictive analytics to understand and retain customers. Businesses can customize retention strategies, promoting loyalty and increasing total profitability, by predicting probable defections.

C) System for Predicting Trends

Being aware of market trends is essential in the fast-paced world of business. Predictive analytics is used by the Sri Lankan tea business to foresee changes in consumer preferences. Similar to this, a trend prediction system predicts future patterns in a variety of industries by utilizing machine learning. It gives companies the insight they need to stay ahead of the competition, adjust to changing market dynamics, and maximize their resources.

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D) System for Predicting Inventory

Effective inventory management is essential for smooth operations, both in and outside of the tea sector. Large-scale farming changed Sri Lanka's terrain, and today's companies depend on inventory prediction systems to maintain the right amount of inventory. These solutions help organizations manage proper inventory levels, avoid delays, and increase overall operational efficiency by utilizing cutting-edge technology and data analysis. As with the tea industry, effective inventory management is crucial to increasing earnings and cutting costs across a range of industries.

II. LITRETURE REVIEW

With the help of predictive analytics, which has become increasingly popular across a range of industries, researchers and practitioners can now accurately predict trends, sales prices, churn, and inventory levels. This review includes ideas from multiple important research papers to cover the wide range of information currently available on these subjects.

The dynamic nature of tea markets demands accurate trend prediction in order to facilitate well-informed decision-making. Ratto showcased the potential of integrative models in market trend prediction by proposing an ensemble technique that blends technical analysis and machine learning[1]. Similarly, Patel demonstrated the suitability of data-driven approaches in this situation by forecasting stock movements using Trend Deterministic Data Preparation and machine learning techniques[2]. Song examined machine learning techniques for predicting market trends, highlighting the importance of data-driven tactics even more. Furthermore, a comparison research of supervised machine learning algorithms for stock market trend prediction was carried out by Kumar, providing insightful information about the effectiveness of various approaches[3].

The field of customer churn prediction has greatly benefited from machine learning. A customer churn prediction system was developed by Lalwani using machine learning techniques[4]. This system is very useful for industries such as telecommunications. The domain was enhanced by Qureshi and Ahmad, by the development of churn prediction models tailored for telecom subscribers[5], [6]. Furthermore, Dalvi used logistic regression and decision trees to study customer churn prediction in the telecom sector, demonstrating the usefulness of these methods for reducing customer attrition[7].

Maintaining supply chain operations depends on effective inventory management. Ntakolia highlighted the necessity for transparent predictive models by proposing an explainable machine learning model for material backorder prediction in inventory management[8]. This field was expanded by De Santis, who used machine learning to forecast material backorders, leading to improved inventory control techniques[9]. Additionally, Qi provided a thorough method to address this difficult problem by presenting a workable end-to-end inventory management strategy via deep learning[10].

Forecasting sales prices is essential for making business decisions. Mentzer and Moon highlighted the significance of precise forecasts for efficient sales management and promoted a demand management approach to sales forecasting[11]. Cheriyan demonstrated the promise of data-driven approaches in this field by utilizing machine learning algorithms for intelligent sales prediction[12]. The interpretability of machine learning models in sales forecasts was investigated by Bohanec, emphasizing the necessity of predictive model transparency[13]. Schmidt improved this field even further by bringing in a machine learning-based method for predicting restaurant sales[14]. Niu demonstrated the possibility of sophisticated machine learning approaches in retail sales prediction by using the XGBoost algorithm and feature engineering to predict sales[15]. This comprehensive literature review examined the integrated system's components, including trend prediction, sales projection, inventory management, and churn anticipation using machine learning. After exploring how each element contributes to an integrated system aimed at enhancing tea production and its associated components. These studies collectively provide insights into the development of a holistic system for optimizing tea factories.

III. RESEARCH PROBLEM

In the fast-paced and highly competitive tea industry, managing client turnover, forecasting market trends, maximizing sales prices, and effectively controlling inventory are just a few of the difficulties faced by tea factories. Even if the current study article offers a thorough methodology that makes use of cutting-edge machine learning techniques to address these issues, improving the sustainability and resilience of tea factories is still vitally important.

IV. METHODOLOGY

A) Data gathering for dataset training

The successful development and implementation of the four prediction systems, namely the Sales Price Prediction System, Churn Prediction System, Trend Prediction System, and Inventory Prediction System, depend significantly on the quality and relevance of the data collected. In this section, we elaborate on the data gathering process, emphasizing the vital role of Adaradeniya Tea Factory as the primary data source. Adaradeniya Tea Factory is a leading Sri Lankan Tea Manufacturer.

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1) Churn Prediction System

The Churn Prediction System is reliant on customer-related data for the accurate prediction of churn. The necessary information is collected from Adaradeniya Tea Factory.

2) Trend Prediction System

Data for the Trend Prediction System, which focuses on forecasting sales trends, is sourced from the tea factory's transactions.

3) Inventory Prediction System

For the Inventory Prediction System, the data acquisition process is rooted in Adaradeniya Tea Factory's records.

4) Sales Price Prediction System

For the Sales Price Prediction System, the data acquisition process is rooted in the tea factory's transactions

All data is meticulously collected from Adaradeniya Tea Factory which is a leading Sri Lankan tea Manufacturer to ensure accuracy and relevance to the context of the tea industry. The subsequent stages of our methodology encompass data cleaning, preprocessing, feature engineering, and the selection of appropriate models for each prediction system. This holistic approach ensures that our models are well-informed and capable of making accurate forecasts and predictions.

B) System Overview

The quality and applicability of the data gathered are critical to the development and operation of the four prediction systems, which are the Sales Price Prediction System, Churn Prediction System, Trend Prediction System, and Inventory Prediction System. Going into further details about the data collection procedure in this section, highlighting the significance of Adaradeniya Tea Factory as the main data source. The figure 1 despites the overall system overview diagram.

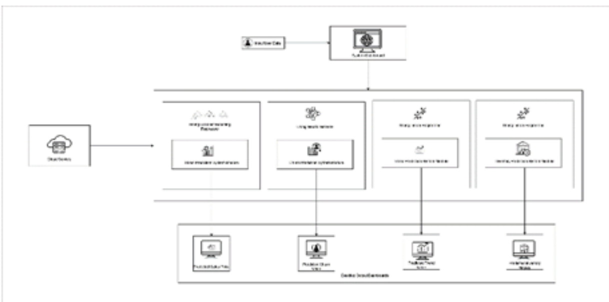

Figure 1: Overall System Overview diagram

1) Churn Prediction System for Sri Lankan Tea Factories

The research focuses on the Sri Lankan tea sector's ability to forecast customer turnover using data preparation and models. Data preparation involves collecting a large amount of consumer datasets, preprocessing and data preparation using data mining procedures. The initial phase involves identifying the best models for accurate churn prediction, selecting appropriate modeling techniques based on the data context, and validating the model's prediction ability.

Effective data preparation is crucial for predictive modeling, with the OneHotEncoder from Scikit-learn encoding categorical information like "purchase Chanel" and "tea preferences" for better integration into regression models. The StandardScaler's feature scaling function normalizes numerical attributes, ensuring consistency in their impact. The train_test_split function splits the dataset into training and testing sets for accurate evaluation of the model's performance on untested data.

Various machine learning techniques, such as decision trees, neural networks, and linear regression, were examined for their effectiveness. The neural network approach was found to be the most accurate, making it the primary model for better churn prediction. This choice emphasizes the importance of applying cutting-edge strategies to gain a deeper understanding of consumer behavior and enhance the ability to spot likely churn events. The churn prediction model's overall system architecture is depicted in Figure 2.

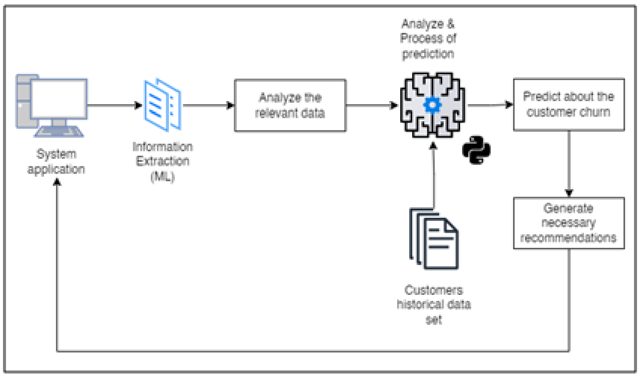

Figure 2: Churn Prediction System Overview diagram

2) Trend Prediction System for Sri Lankan Tea Factories

This study focuses on forecasting tea grade trends in the Sri Lankan tea industry, aiming to provide valuable insights for tea factories. The system begins with a real transaction dataset from a Sri Lankan tea factory, which undergoes meticulous preprocessing to ensure data reliability and accuracy. The heart of the system lies in its time series analysis, which arranges the data chronologically to understand and forecast tea grade trends. The dataset is split

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into training and testing sets using Scikit-learn's train_test_split function for accurate evaluation of the model's performance on unseen data.

Linear regression is utilized to identify and model linear trends within the tea grade data, analyzing historical data to establish relationships between time and tea grade trends. ARIMA (AutoRegressive Integrated Moving Average) models are considered to capture complex temporal patterns in the data, considering both short-term and long-term trends.

The system evaluates the performance of both the Linear Regression and ARIMA models using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R2). The Linear Regression model consistently outperforms the ARIMA model across all evaluation metrics, indicating a better fit to the data and a stronger ability to explain the variability in tea production trends.

The Trend prediction model's system architecture is depicted in Figure 3.

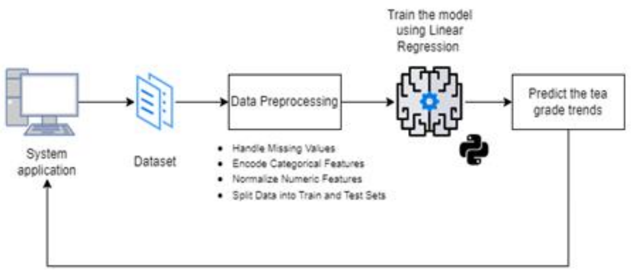

Figure 3: Trend Prediction System Overview diagram

In conclusion, this system considered both Linear Regression and ARIMA models for tea trend prediction in the Sri Lankan tea industry. While both models were evaluated, the Linear Regression model emerged as the superior choice, showcasing better predictive performance and greater suitability for forecasting future tea trends.

3) Inventory Prediction System for Sri Lankan Tea Factories

The implementation of an Inventory Prediction System tailored for Sri Lankan Tea Factories represents a significant advancement in inventory management. In this system, a machine learning model based on the linear regression algorithm is the key component. The model's foundation lies in historical inventory data, which was used for training.

This approach offers a proactive solution for optimizing inventory management, reducing waste, and ensuring that inventory levels align with market demand efficiently. By leveraging past data, the linear regression model has learned to predict inventory movements and trends, providing valuable insights that guide decision-making within the tea factory. The model offers a data-driven approach, allowing for continuous monitoring and fine-tuning to ensure its predictions remain accurate.

Incorporating real-time data updates, performance assessments, inventory thresholds, and user training will further enhance the system's effectiveness. With this Inventory Prediction System, Sri Lankan Tea Factories can improve inventory control, reduce operational costs, and maintain the flexibility needed to meet dynamic market demands, ultimately contributing to the sustainability and success of the tea industry in Sri Lanka.

The Inventory prediction model's overall system architecture is depicted in Figure 4.

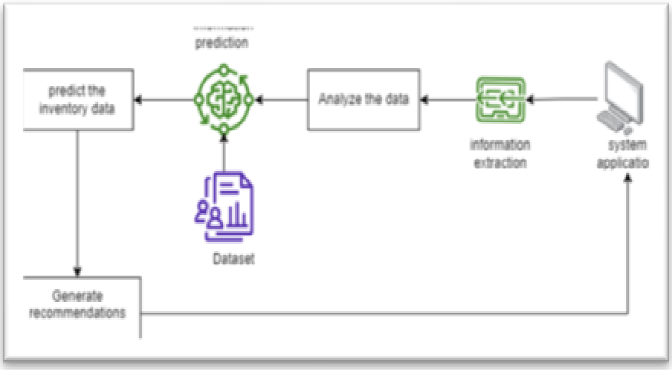

Figure 4: Inventory Prediction System Overview diagram

4) Sales Prediction System for Sri Lankan Tea Factories

This study uses real transactions data to forecast tea sales prices using a methodology that includes data preprocessing, model training, and evolution. The data is collected, processed, and transformed into a knowledge representation format for machine learning algorithms. The model is trained to uncover patterns between sales and factors like product price, marketing campaigns, and economic conditions. Scikit-learn's OneHotEncoder is used to encode categorical features, while StandardScaler's feature scaling function normalizes numeric attributes.

Data is divided into training and testing sets using Scikit-learn's train_test_split function. Three distinct regression models are employed: Gradient Boosting Regressor, Random Forest Regressor, and XGBoost Regressor. The R2 score is used to assess each model's performance, and hyperparameter configurations are tailored for the Gradient Boosting Regressor to optimize its predictive capabilities. This comprehensive approach provides valuable insights into the potential of machine learning techniques for predicting future sales.

Figure 5 shows an overview of the sales prediction system.

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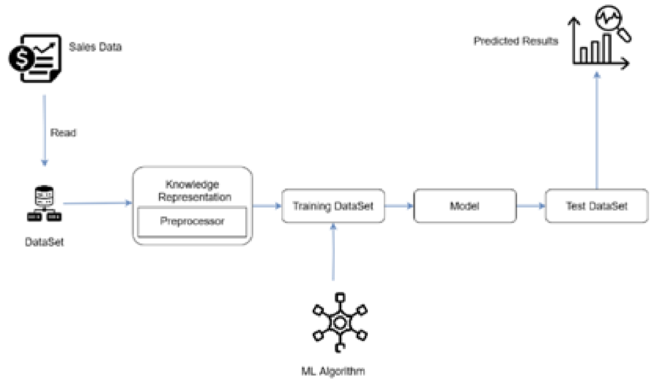

Figure 5: Sales Price Prediction System Overview

V. RESULT AND DISCUSSION

A) Churn Prediction System for Sri Lankan Tea Factories

Utilized two machine learning methods, decision trees and neural networks, to train the churn prediction model. Decision trees and neural networks are two supervised machine learning algorithms that can be used to predict the probability of an occurrence, like the possibility of churn. After quickly gathering the data or information offered by their clients, they might formulate and provide an algorithm. Neural networks function similarly to the way human brains receive information, process it, and then generate output. Despite the fact that this approach seems quite simple and easy to understand, it is actually lot more complex. ANNs can be taught using a variety of tools and applications to produce output that is more accurate, flexible, and reliable. The decision tree model provided a accuracy score of 0.7625, and the neural network model provided a score of 0.8025, based on 7030 customer details and 13 data attributes. Therefore, the final decision was to use the neural network for the churn prediction model because of its high accuracy score. Figure 4 shows the final accuracy of the ANN model which was created for the churn prediction model.

	precision	recall	f1-score	support
0	0.85	0.73	0.78	1033
1	0.76	0.87	0.81	1033
accuracy			0.80	2066
macro avg	0.81	0.80	0.80	2066
weighted avg	0.81	0.80	0.80	2066

Figure 6: ANN model accuracy

B) Trend Prediction System for Sri Lankan Tea Factories

The study evaluated the performance of Linear Regression (LR) and ARIMA models in forecasting tea grade trends in the Sri Lankan tea industry. The LR model showed exceptional performance, with a small overall error in predictions and an ARIMA MAE of 10.63. The ARIMA model, on the other hand, provided reasonably accurate predictions but exhibited slightly larger errors. The ARIMA MSE of 2028.54 indicated a slightly higher overall prediction error than the LR model, with an average deviation of approximately 38.53 units from the actual values. The ARIMA R2 value of 0.9997 indicated a strong ability to explain the variability in tea grade trends, but it was slightly lower than the LR model. Moreover, the LR R2 value of 0.9999 is exceptionally close to 1, demonstrating the model's high accuracy in explaining the variability in tea grade trends. The results of this study highlight the superiority of the LR model in forecasting tea grade trends in the Sri Lankan tea industry, demonstrating its potential as a valuable tool for making informed decisions regarding production, inventory management, and marketing strategies. The figures in Figure 7, Figure 8, Figure 9 despites the LR model's overall performance evaluation, Arima model's overall performance evaluation, shows side-by-side comparison plot of actual tea grade data and predictions made by the Linear Regression model (BM tea grade) respectively.

```
Mean Squared Error (MSE): 2028.5443529689062
Mean Absolute Error (MAE): 38.52503718268357
R-squared (R2): 0.999743825743455
```

Figure 7: LR model's overall performance evaluation

```
LR MSE 23.971811977564865
LR MAE 10.634406171907585
LR R2 0.9999255804782728
```

Figure 8: Arima model's overall performance evaluation

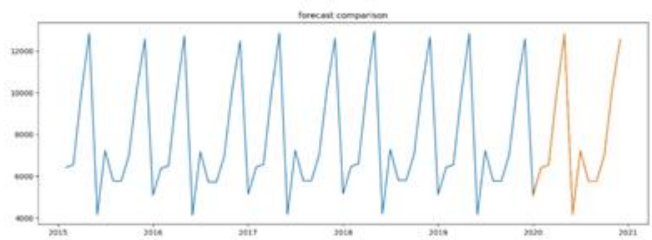

Figure 9: Shows side-by-side comparison plot of actual tea grade data and predictions made by the Linear Regression model (BM tea grade)

C) Inventory Prediction System for Sri Lankan Tea Factories

In this study, the task at hand involved the prediction of tea inventory. Employing the linear regression approach, a dedicated model was developed for each tea variety with the

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overarching objective of facilitating more effective stock management for tea businesses.

Figure 10 despites the Item (BOP1- tea grade) prediction accuracy of inventory prediction System.

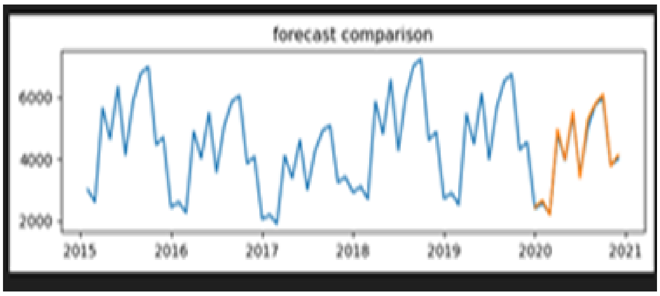

Figure 10: Item (BOP1- tea grade) prediction accuracy of inventory prediction System

The findings proved noteworthy. On average, the linear regression models displayed a commendable ability to predict tea inventory levels, as indicated by an R-squared (R^2) value of approximately 0.99, a mean squared error (MSE) of approximately 28.62, and a mean absolute error (MAE) of around 11.92. However, it should be noted that the accuracy of these predictions exhibited variations contingent upon the specific tea variety, underscoring the unique prediction challenges associated with each.

Moreover, our study shed light on the inherent limitations of linear regression. This modeling technique presupposes linear relationships, which may not consistently align with the complexities of real-world data. Notably, factors such as data quality and the presence of outliers exerted substantial influence on the reliability of our predictions.

In response to these findings, it was recommended that the exploration of more sophisticated modeling strategies and the incorporation of additional tea-related features could potentially bolster forecasting accuracy. The field of tea inventory prediction offers ample room for further research and improvement.

Figure 11 despites the LR model's item performance evaluation.

Figure 11: LR model's item performance evaluation

D) Sales Prediction System for Sri Lankan Tea Factories

This study, carried out a study of pricing prediction models on a dataset that included data on tea sales. To manage missing values, data type conversions, and feature engineering, the dataset underwent preprocessing. Three separate regression models were used to predict tea prices after preprocessing. The models of choice were:

1. *Gradient Boosting Regressor:* This model suited the test data reasonably well, as seen by its R-squared score of roughly 0.7854. Its Mean Squared Error (MSE) was 140451.27 and its Mean Absolute Error (MAE) was 135.42. This model showed inconsistent performance in cross-validation over various folds, with an average R-squared score of roughly 0.2288.

2. *Random Forest Regressor:* With an R-squared score of around 0.9033, the lowest MAE of 115.71, and an MSE of 63280.96 on the test data, the Random Forest model fared better than the other models. Its performance was likewise consistent according to cross-validation results, which had an average R-squared score of roughly 0.5526.

3. *XGBoost Regressor:* Using test data, the XGBoost model produced an R-squared score of around 0.8625, an MAE of 127.18, and an MSE of 90006.61. The model's performance varied among folds, according to cross-validation findings, with an average R-squared score of roughly 0.1234.

Figure 12 despites the results of the model training for sales price prediction system.

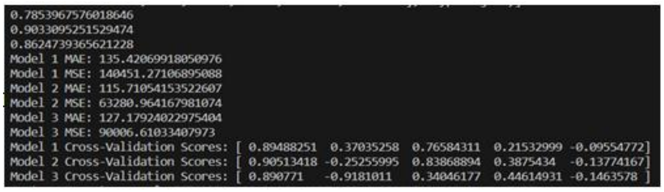

Figure 12: Results of model training for Sales price prediction

Then took into analyze a number of evaluation factors, including cross-validation scores, MAE, R-squared, and MSE, in order to choose the optimal model. To determine a composite score for each model, utilized a weighted combinations of these parameters.

The formula to calculate the combined score for a model is: Combined Score = (Weight_R-squared * R-squared) + (Weight_MAE * MAE) + (Weight_MSE * MSE) + (Weight_CV * Average Cross-Validation Score)

So, the Combined Score for Model 1 = (0.4 * R-squared) + (0.2 * MAE) + (0.2 * MSE) + (0.2 * Average Cross-Validation Score)

The Random Forest Regressor was determined to be the most effective model for predicting tea prices based on the total scores.

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The Random Forest model was also subjected to feature importance analysis, which shed light on the relative value of different features in predicting tea prices. The main characteristics that affected the model were "year," "No of Bags," "Lot No," and "BATUWANGALA." The factorsinfluencing tea pricing can be better understood by industry stakeholders with the use of these insights.

Figure 13 demonstrates the Out-of-Bag (OOB) improvement exhibited by a random forest regressor in relation to the number of estimators quantifies.

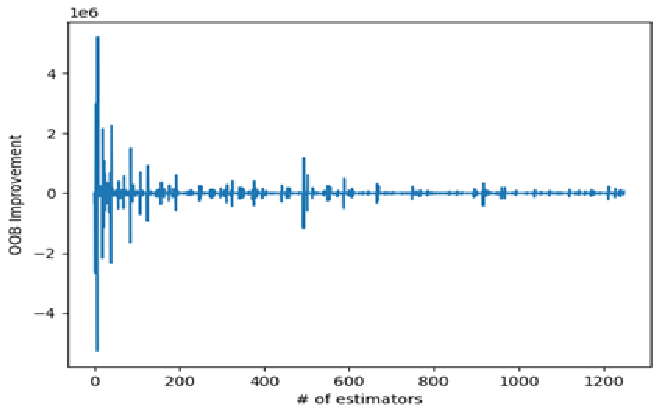

Figure 13: The Out-of-Bag (OOB) improvement exhibited by a random forest regressor in relation to the number of estimators quantifies

VI. CONCLUSION

In this study, a unique management system for a tea factory or business using advanced machine learning techniques was developed. Neural networks were used for customer churn prediction, gradient boosting regression was used for sales prediction, and linear regression was used for both trend and smart inventory management. Our findings illustrate how well these models may be used to enhance several business functions. They offer precise churn predictions, accurate sales estimations, effective inventory management, and trend predictions. Although the results are positive, there are a few important limitations that must be aware of. The models' dependence on historical data and absence of other variables may limit their capacity to the changes in the market. However, these limitations may also serve as an entry point for additional research. For instance, the Smart Inventory Management System might find it difficult to adapt to unexpected events in the supply chain and might profit from real-time data integration. Furthermore, the Trend Prediction System's dependence on significant historical data may provide difficulties for more recent or specialized items, and predictions may be affected by the absence of outside events like marketing efforts. Even still, these limits open new possibilities for research. In conclusion, our unique management system, which is powered by advanced machine learning, marks an important improvement in the efficiency of operations for tea factories. By recognizing our limitations and setting out a plan for future research and hope to make improvements in predicting accuracy and flexibility. This study offers a novel approach to business operations, improves the tea industry, and provides evidence of the fascinating potential of data-driven management in a variety of industries.

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