# Predicting Tea Quality Based on Antioxidant and Polyphenol Content Using Ensemble Machine Learning Model

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***Abstract*—Made from Camellia sinensis, tea is highly valued for numerous health benefits and rich phytochemical makeup. This research aims to determine whether antioxidant and polyphenol levels may be used to predict the quality of tea using machine learning techniques. The main objective is to improve prediction accuracy using ensemble models that integrate the Random Forest and Decision Tree methods. The results showed the effectiveness of the ensemble model, with up to 99.89% accuracy in polyphenol and antioxidant dataset tea quality prediction. The proposed research highlights the potential of machine learning to enhance the efficiency of tea production procedures, guarantee uniformity in product quality, and propel scientific comprehension of tea's nutritional and health advantages. By utilizing cutting-edge procedures, the tea industry may improve manufacturing processes and offer consumers high-quality goods enhanced with health-promoting phytochemicals.**

***Index Terms*—Tea Quality Prediction, Quality Control, Machine learning, Ensemble Model.**

## I. INTRODUCTION

'Camellia sinensis' (Tea) is one of the ancient and most widely consumed drinks in India, China, Japan, and the Western world [1]. Tea is an evergreen shrub that grows well at an optimum temperature of 15-20°C. Tea leaves contain several phytochemical compounds, often broken down to form new compounds during processing. Tea leaves are abundant in Theobromine, theophylline, polyphenols, lignin, organic acids, thiamine, amino acids, and caffeine [2]. It also contains flavonoids and volatile terpenes, which contribute to the aroma of the tea after brewing [3]. Green tea contains polyphenolic catechins such as Epicatechin (EC), Epicatechin-3-gallate (ECG), epicatechin-3-gallate (EGCG), and Epigallocatechin (EGC) [4]. Tea can be classified into four types, namely Green Tea (non-fermented), Black Tea (fermented), Oolong Tea (partially fermented), and White Tea (most minor processing) based on its processing methods. Green tea is produced by tearing the freshly plucked green leaves, steaming, rolling, and drying them. This process undergoes minimal processing and thus contains about 80-90% catechin and 10% flavonoids [5]. A mild pale green or yellow liquor is achieved when this non-fermented tea is brewed. Black tea, the most widely consumed type, involves further processing. Further steps such as aeration, withering, and oxidation/fermentation are taken. These leaves, when infused, produce a light to dark brown-coloured beverage with a sweet flavoured aroma [6]. During fermentation, the total flavonoid content increases to 50-60%, catechin fermented is condensed, and polymeric polyphenols theaflavins (TFs) and thearubigins (TRs) are produced. Catechin content is about 20-30%, and TFs and TRs range about 10%, respectively. Four main classes of tea are distinguished by leaf size: Whole Leaf, Broken, Fannings, and Dust. The largest leaf categories are whole (1-2 cm), followed in size order by broken (1 cm), fannings (1/8 inch), and dust. CTC (Crush Tear Curl) tea comprises Broken Fannings and Dust, whereas orthodox tea, or black tea, contains all four grades. These days, machine learning is a crucial instrument for raising the accuracy of the assessment of tea quality [7]. This study uses machine learning to compare the antioxidant and polyphenol contents of CTC, black, and green tea. This paper aims to improve quality control techniques and offer insights into the health advantages of various tea kinds by fusing data from chemical analyses with sophisticated algorithms.

## II. LITERATURE SURVEY

Hui Jiang et al. [8] assessed the amount of tea polyphenols in green tea, using a customized color-sensitive sensor tuned using the Ant Colony Optimization (ACO) technique. After processing the sensor data using an Extreme Learning Machine (ELM), the correlation coefficient (RP) was 0.8035, and the RMSEP was 1.6003%.

Sarmin Sultana Snigdha et al. [9] developed a CNN model-based image processing system that tracks the quality of tea, such as DenseNet121 and InceptionV3. InceptionV3 attained 99.84% training accuracy, although the dataset's size and image quality constraints make more study and dataset enlargement necessary.

Lakshmi Prasad Bhuyan et al. [10] examined The biochemical components and antioxidant activity of 60 tea samples, revealing that nitrite scavenging was more active. Antioxidant activity and theaflavin were connected, and superior tea was produced in places like Upper Assam. Subsequent studies ought to concentrate on the impact of flavonoids on the antioxidant qualities and quality of tea.

Retinderdeep Singh et al. [11] created a CNN model with 84.5% classification accuracy trained on 900 high-resolution pictures of tea leaf dots. This technique makes it possible to identify tea leaf illnesses quickly. It may also be used for IoT integration, drone monitoring, and smartphone apps for farmers.

R.Vasanthi et al. [12] created an Internet of Things system that uses sophisticated sensors to measure temperature, humidity, and pH to determine if food is fresh or spoiled. By analyzing sensor data, machine learning techniques such as logistic regression improve the assessment of food quality and lower the risk of contamination, spoiling, and waste.

Md. Johirul Islam Tutul et al. [13] proposed an IoT-based system using temperature, humidity, and gas sensors to monitor food freshness in real-time via a web dashboard. Machine learning algorithms accurately assess food quality, reduce waste, enhance management, and ensure personal and commercial safety.

Elia Henrichs et al. [14] suggest a multi-level observer/controller system that uses sophisticated sensors and machine learning to monitor the conditions of packed food. The sensor sample rates are adjusted according to the environment and energy. Adaptive machine learning and digital twins will be used in future research to improve performance.

S. Jayanthy et al. [15] suggest that CNN and SVM algorithms are used to categorize tea buds and identify leaf illnesses. Compared to SVM, CNN models (DenseNet-121, DenseNet-201) had greater accuracy (96.703% and 96.923%). Drone integration in the future may automate tea monitoring, saving money and manpower.

Seyed Mohammad Taghi Gharibzahedi et al. [16] suggested combining machine learning with electronic sensing platforms (e-nose, e-tongue, and e-eye) to analyze tea quality quickly and precisely. These systems categorize tea according to its sensory and chemical characteristics; future developments will concentrate on sensor performance and feature extraction methods.

Huajia Wang et al. [17] investigate that by employing computer vision and machine learning for sophisticated cultivation and processing, the tea business is being transformed. Disease detection and bud identification are two important uses, and future developments will likely centre on UAVs and deep learning to solve issues with sustainable tea production.

Pengfei Zheng et al. [18] evaluate image processing and visible-near-infrared spectroscopy (vis-VIS-NIR) for the fermentation of oolong tea. Through 97.14% prediction accuracy, their study revealed that classical SVM models outperformed deep learning, opening the door for non-intrusive online monitoring of tea processing across different varieties and seasons.

## III. MATERIALS AND METHODS

### A. *Samples:*

Three types of tea samples, green tea, black tea, and CTC samples, were procured from the local market of Kolkata. For each grade, an analysis was done in duplicate.

### B. *Chemicals and Reagents :*

For the determination of the total phenolic content (TPC), Folin-Ciocalteu's phenol reagent (Merck Chemicals), gallic acid (99% purity, Sigma), and anhydrous sodium carbonate (99% purity) were used. Ferric Chloride, 2,4,6-tripyridyl-s-triazine, HCl, and acetate buffer were employed to determine the antioxidant activity.

### C. *Extraction of Polyphenols :*

The extraction of polyphenols was done as described by the International Organization for Standardization (ISO) 14502-1 and was used [19]. 1mg of each sample was weighed in a test tube, and 5 mL of 70% methanol was added at 70 °C. The methanolic extract was heated at 70 °C and vortexed for about 10 min. Next, the extract was cooled at 25 °C and centrifuged at 5000rpm for 10 min. The supernatant was allowed to decant. These steps were repeated twice, and the total volume was pooled together and adjusted to 10 mL with cold 70% methanol. 1 ml of this concoction was diluted 100 times, and the OD was measured.

### D. *Determination of Total Polyphenol Content :*

The total polyphenol content (TPC) was determined by spectrophotometry, using gallic acid as standard, according to the method described by the International Organization for Standardization (ISO) 14502-1 [19]. Briefly, 1.0 mL of the diluted sample extract was transferred in duplicate to separate tubes containing 5.0 mL of a 1/10 dilution of Folin-Ciocalteu's reagent in water. Then, 4.0 mL of a sodium carbonate solution (7.5% w/v) was added. The tubes were then allowed to stand at room temperature for 60 minutes before absorbance at 765 nm was measured against water. The TPC was expressed as gallic acid equivalents (GAE) in g/100 g material. The concentration of polyphenols in samples was derived from a standard curve of gallic acid ranging from 10 to 50 µg/ml [20].

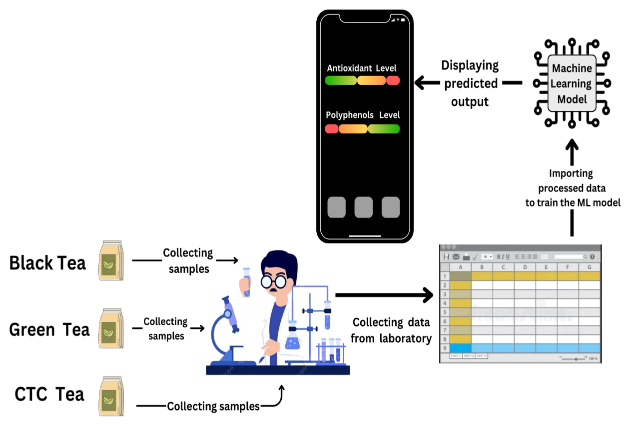


Fig. 1. Proposed Tea Quality Monitoring Architecture

### E. Designing a proposed model using machine learning :

Fig. 1 shows that to determine the polyphenol and antioxidant content of green tea, black tea, and CTC tea, we suggest using an ensemble model that combines many machine learning methods, such as Random Forest, Decision Tree algorithms, and Linear Regression. Our strategy is to improve prediction accuracy by minimizing the shortcomings of each model while utilizing its strengths. The Random Forest and Decision Tree models in the ensemble model are trained independently using pre-processed datasets that include measurements of polyphenol and antioxidant concentrations along with relevant tea-specific features. These models capture the specific connections found in the data: While Decision Trees are especially effective at capturing complicated decision boundaries, Random Forests prevent overfitting by combining predictions from many trees trained on different subsets of the data. A Voting Regressor is used to aggregate each of their forecasts and produce a final assessment of tea quality. By combining the two models' combined predictive power, this ensemble approach frequently produces better performance metrics than using each model separately. Standard regression measures like Model Accuracy, Precision, Recall, and F1 Score are used to evaluate the ensemble model. The F1-score, precision, and recall are calculated to evaluate the model's performance for classification tasks. Our tests show that the Random Forest and Decision Tree ensemble performs robustly across various assessment parameters, regularly outperforming individual models. The ensemble model can enhance quality control procedures in tea manufacturing by providing real-time quality assessments of tea samples once they have been trained and verified. By adjusting to fresh data and changing patterns in the evaluation of tea quality, continuous learning techniques guarantee that the model will continue to function well over time. Our ensemble model, which combines Random Forests' resilience with Decision Trees' interpretability, provides a reliable and effective method for evaluating tea quality. This method contributes to improvements in the tea industry's operations and scientific research by improving the effectiveness of quality control procedures and offering insightful information about the health advantages and flavour profiles of various tea varieties.

## IV. METHODOLOGY

Our approach includes multiple critical processes to estimate the quality of CTC tea, black tea, and green tea based on their polyphenol and antioxidant content [21]. Data collection is our first step, and we compile extensive datasets with measurements of antioxidant and polyphenol contents for different tea samples. The data is cleaned during pre-processing to manage missing values using imputation techniques such as mean or median imputation. Inconsistencies are also corrected, and outliers are eliminated.

To prevent the numerical features from unduly affecting the model, they are normalized to ensure they are on a similar scale. Label encoding transforms categorical variables into a numerical format, such as tea. We choose the Random Forest, Decision Tree, and Linear Regression techniques for model creation. To comprehend the linear correlations between variables and tea quality, one might start with Linear Regression. Decision Trees identify non-linear correlations and

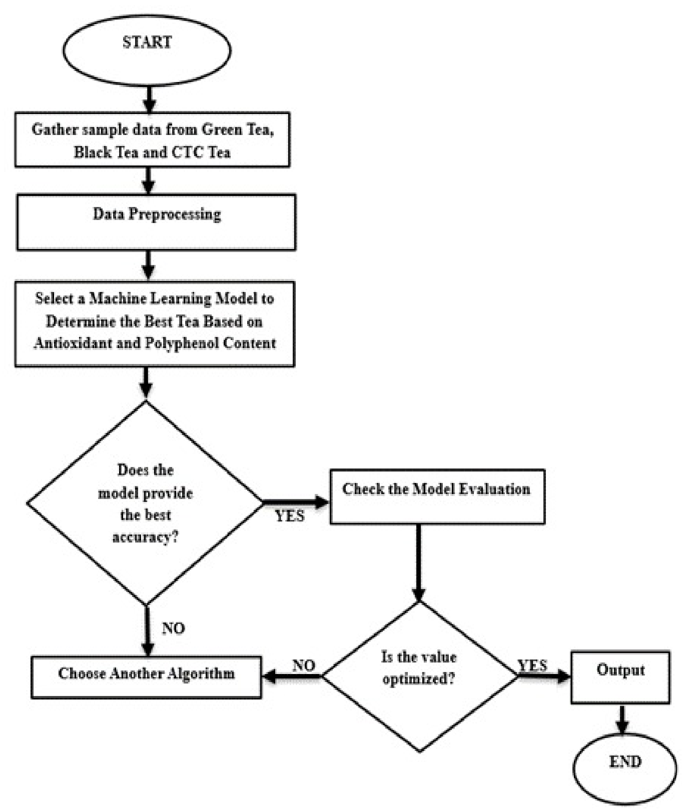


Fig. 2. Working flowchart of Tea Quality Monitoring

decision boundaries in the data. Random Forests aggregate several Decision Trees to improve robustness and minimize overfitting. Using a Voting Regressor to average the forecasts of Decision Tree and Random Forest models, our ensemble model combines their predictions to generate a final estimate of tea quality. We use an 80/20 split to divide the dataset into training and testing sets so the model is tested on unseen data and learns from enough data [22]. The training set trains the Random Forest and Decision Tree models. Cross-validation is used to optimize the hyperparameters to improve performance. The models are initially run using default hyperparameters; however, by adjusting parameters like the number of trees, maximum depth, and minimum samples per leaf, the accuracy and efficiency of the results will be increased.The Voting Regressor is then used to aggregate the predictions of the trained models. We divide the dataset into training and testing sets (usually an 80/20 split) to make sure the model gets enough data to learn from and is assessed on Regression measures like Model Accuracy, Precision, Recall, and F1 Score are used in model evaluation to evaluate how well the model predicts continuous variables like polyphenol concentrations. To assess the model's performance in classification tasks, we calculate precision, recall, and F1-score, as shown in Fig. 2. Our tests show that the ensemble model achieves the most excellent performance across all assessment metrics, consistently outperforming individual models. The ensemble model is implemented for real-time quality evaluation of tea samples after they have been trained and verified. It then integrates into quality control processes in environments where tea is produced. The model is designed to be effective over time by including continuous learning approaches that allow it to adjust to new data and changing patterns in evaluating tea quality. The model may remain accurate while recognizing new patterns with this periodic retraining technique. This approach improves the precision and dependability of quality evaluations. It provides insightful information about the health advantages and flavour characteristics of various tea varieties, assisting in the growth of scientific research and industry practices related to the tea business.

## V. RESULT ANALYSIS

Results were represented in the graph mentioned in Fig. 3, where the highest polyphenol content was found in green tea, measuring 13.2mg/ml GAE; Black tea, measuring 12.31 mg/ml GAE, followed by CTC, measuring 8.58 mg/ml GAE.

### A. Polyphenol Content:

TABLE I
PERFORMANCE PARAMETER OF DIFFERENT MACHINE LEARNING ALGORITHMS BASED ON POLYPHENOL CONTENT

| Algorithms | Accuracy (%) | Obtained Precision | Obtained Recall | Obtained F1 Score |
|---|---|---|---|---|
| Linear Regression | 53 | 0.55 | 0.52 | 0.53 |
| Random Forest | 95 | 0.93 | 0.94 | 0.93 |
| Decision Tree | 94 | 0.92 | 0.93 | 0.92 |
| Ensemble Model (RF+DT) | 99.89 | 0.99 | 0.99 | 0.99 |

### B. Antioxidant Content:

The antioxidant potential of the different varieties of tea was estimated by the FRAP method in this study, represented

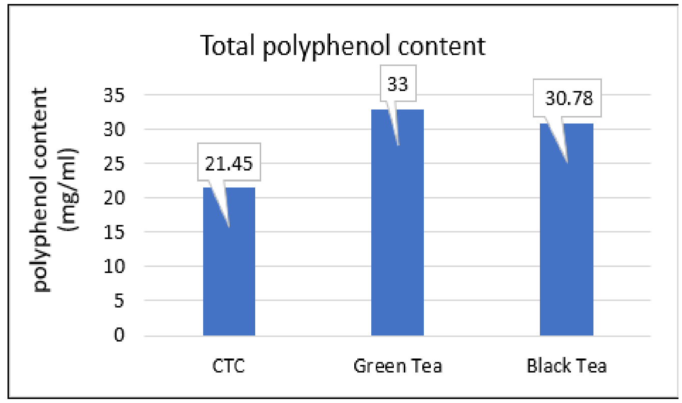


Fig. 3. Polyphenol content of different grades of Tea

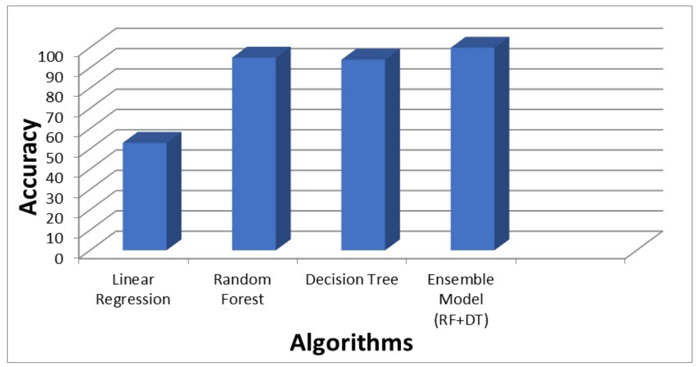


Fig. 4. Accuracy of Tea Quality Prediction Model Based on Polyphenol Value

TABLE II
PERFORMANCE PARAMETER OF DIFFERENT MACHINE LEARNING ALGORITHMS BASED ON ANTIOXIDANT CONTENT

| Algorithms | Accuracy (%) | Obtained Precision | Obtained Recall | Obtained F1 Score |
|---|---|---|---|---|
| Linear Regression | 96 | 0.94 | 0.95 | 0.94 |
| Random Forest | 98 | 0.97 | 0.98 | 0.97 |
| Decision Tree | 95 | 0.93 | 0.94 | 0.93 |
| Ensemble Model (RF+DT) | 99.89 | 0.99 | 0.99 | 0.99 |

in Fig. 5. The highest value was of green tea, measuring 1.56 µg/ml, followed by black tea, measuring 0.88 µg/ml, and CTC, measuring 0.72 µg/ml.

**Linear Regression:** An essential statistical technique for simulating the relationship between a dependent variable and one or more independent variables is linear regression. It assumes a linear relationship between the variables, meaning that changes in the independent variables correspond to proportionate changes in the dependent variable. The equation for the Linear Regression model is:

$$y = \beta_0 + \beta_1 x + \epsilon \quad (1)$$

Where:
$y$ is the dependent variable (e.g., tea quality)
$x$ is the independent variable (e.g., polyphenols or antioxidant content)

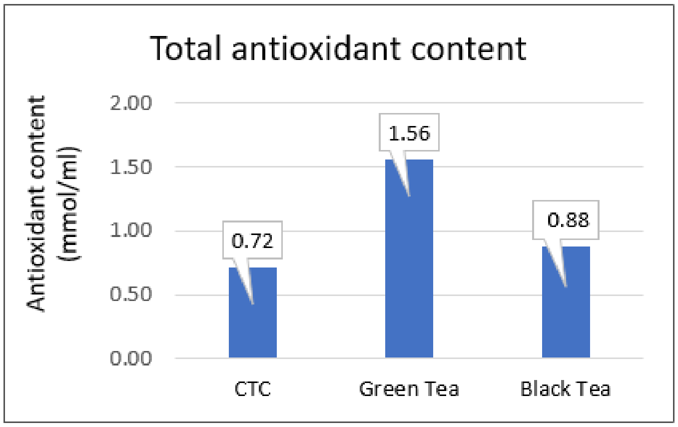


Fig. 5. Antioxidant content of different grades of Tea.

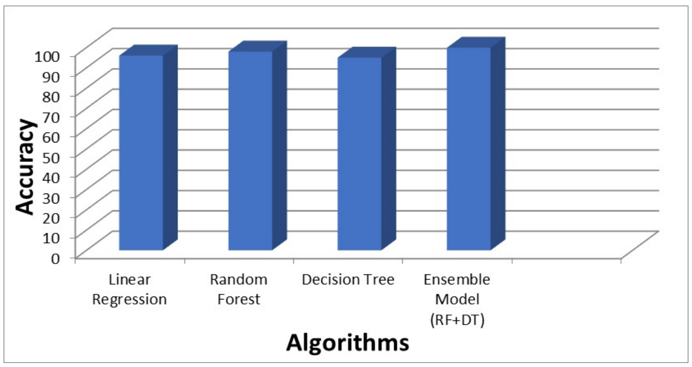


Fig. 6. Accuracy of Tea Quality Prediction Model Based on Antioxidant Value

$\beta_0$ is the intercept or constant term, which represents the expected value of $y$ when $x = 0$
$\beta_1$ is the slope coefficient, which indicates the change in $y$ for a one-unit change in $x$.
$\epsilon$ is the error term, representing the variability in $y$ that cannot be explained by the linear relationship with $x$.

**Decision Tree:** A non-linear approach is called a decision tree for regression and classification applications. Dividing the data into subsets according to the input feature values generates a decision tree-like model. An internal node represents a feature, and a leaf node represents a decision rule by a branch and an outcome.

Using a criterion that maximizes information gain or minimizes impurity (e.g., variance reduction for regression and Gini impurity or entropy for classification), the data are split recursively to create the model. The split criterion can be expressed as:

$$\arg\max_j \sum_{i=1}^{m} I(x_{ij} \leq \theta_j) \tag{2}$$

Where:
$j$ is the feature index.
$\theta_j$ is the threshold value for feature $j$.
$I$ is an indicator function that evaluates to 1 if the condition is true and 0 otherwise.
$x_{ij}$ is the value of feature $j$ for sample $i$.

The Decision Tree algorithm divides the data until a predetermined threshold is reached, a minimum number of samples per leaf, or a maximum tree depth. The resulting model is a tree structure, with a decision rule set represented by each path from the root to the leaf.

**Random Forest:** Random Forest is an ensemble learning technique combining several decision trees to increase prediction accuracy and reduce overfitting. Using bootstrap sampling and random subsets of features, each tree in the forest is trained on a random sample of data, utilizing the power of bagging (Bootstrap Aggregating).

The prediction for a regression task is the average of predictions from all trees in the forest:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} T_i(x) \tag{3}$$

Where:
$\hat{y}$ is the predicted value.
$N$ is the number of trees in the forest.
$T_i(x)$ is the prediction from the $i$-th tree.

As each tree in the Random Forest grows on its own, its forecasts are added together to yield a final prediction that is more reliable and accurate. Because it averages out the errors, this approach lowers the risk of overfitting compared to a single decision tree.

**Ensemble Model:** The ensemble model uses a Voting Regressor to aggregate the individual predictions from several models, including Decision Tree and Random Forest. The Voting Regressor usually averages the predictions for regression tasks:

$$\hat{y}_{ensemble} = \frac{1}{M} \sum_{j=1}^{M} \hat{y}_j \tag{4}$$

Where:
$\hat{y}_{ensemble}$ is the final prediction value.
$M$ is the number of models.
$\hat{y}_j$ is the prediction from $j$-th model.

Based on datasets assessing antioxidant and polyphenol levels, our work used an ensemble model integrating Random Forest and Decision Tree algorithms to estimate tea quality. Comparing the assessment criteria to individual models, they showed considerable gains in predicted accuracy. Table 1 shows that the polyphenol dataset yielded scores of 0.53 for Linear Regression and 0.98 and 0.94 for Random Forest and Decision Tree models, respectively, suggesting that the linear relationship was more challenging to represent. With an accuracy of 99.89%, the ensemble model outperformed once more, showcasing its capacity to describe complex interactions and fluctuations in polyphenol content, which is shown in Fig. 4. In a similar vein, Table 2 shows that Linear regression received an accuracy value of 0.96 for the antioxidant dataset. In contrast, decision tree and random forest models received scores of 0.98 and 0.95, respectively. With an accuracy of

99.89%, the ensemble model beat all others, using the advantages of both techniques to increase prediction accuracy. Our ensemble model outperforms earlier established models in terms of prediction accuracy compared to research already published in the literature. These findings demonstrate how well the ensemble model integrates many modelling techniques to produce reliable estimates of tea quality, essential for streamlining manufacturing procedures and guaranteeing product uniformity in the tea sector, as shown in Fig. 6.

## VI. CONCLUSION

In conclusion, to predict tea quality based on antioxidant and polyphenol content, we applied state-of-the-art machine learning techniques in this study [23]. Specifically, we used ensemble models that combine Random Forest and Decision Tree algorithms. Our results demonstrated notable improvements in accuracy when compared to individual models, with the ensemble model achieving up to 99.89% accuracy in both antioxidant and polyphenol datasets. This strong performance highlights the usefulness of combining multiple modeling approaches to handle the complexities of tea quality assessment. By utilizing these advanced algorithms, we can improve the accuracy of assessments of tea quality while also gaining a better understanding of the various chemical compositions and health advantages linked to various types of tea [24]. This research benefits the tea business by enabling efficient manufacturing procedures, guaranteeing consistent product quality, and expanding scientific knowledge of tea's nutritive and health-promoting qualities. In the future, machine learning model development and exploration will be crucial to streamlining tea production methods and enhancing consumer experiences across the globe.

## ACKNOWLEDGEMENTS

This work was supported by the IEM Grant In Aid project and the Center of Excellence for Advanced Communication & Intelligent Computing.

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