Development of Crop Yield Estimation Model using Soil and Environmental Parameters

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Abstract. Crop yield is affected by various soil and environmental parameters and can vary significantly. Therefore, a crop yield estimation model which can predict pre-harvest yield is required for food security. The study is conducted on tea forms operating under National Tea Research Institute, Pakistan. The data is recorded on monthly basis for ten years period. The parameters collected are minimum and maximum temperature, humidity, rainfall, PH level of the soil, usage of pesticide and labor expertise. The design of model incorporated all of these parameters and identified the parameters which are most crucial for yield predictions. Feature transformation is performed to obtain better performing model. The designed model is based on an ensemble of neural networks and provided an R-squared of 0.9461 and RMSE of 0.1204 indicating the usability of the proposed model in yield forecasting based on surface and environmental parameters.

Keywords: crop yield forecasting, regression, data mining, artificial neural network, ensemble learning.

1 Introduction

Farming has a major role in the growth of human civilization as it is the only way to support the increasing food demands. With the growth of human population and settlements, the farmland area decreased and the need of food supplies increased. Advancements in agricultural technologies proven helpful to cater for increased needs and reduced crop loss. Plant genetics, weed and pest control methodologies and fertilizers are employed to overcome the decreasing soil fertility and increase the yield. Weather and soil analysis has provided insight to the parameters affecting the growth and yield and therefore are helpful in identification of suitable crop for a particular weather and land type.

Monitoring of soil and farmland is important as it is helpful in yield estimation and contributes towards economic development and food security of a nation. Remote sensing has proven to be effective in agricultural monitoring, yield forecasting and irrigation scheduling (Weiss, Jacob et al. 2020). These techniques provide flood and other disaster warnings as well as crop growth monitoring and disease spread modeling. The crop production and yield prediction have direct influence on the economics and food management (Hayes and Decker 1996). Estimation of crop yield is of particular interest to various stakeholders: farmers, national government and international institutions to strengthen the food security (Filippi, Jones et al. 2019, Kogan 2019, Kogan, Guo et al. 2019). The crop yield is considered as indicator of productivity which is total harvested mass per unit area. Small farm holders typically focus on yield at farm scale, expecting to increase their financial returns. Whereas government, international organizations and commodity traders are focused to yield estimates at larger scales such as administrative units or national levels. Crop insurer focus towards both small scale and large scale yield estimates.

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in order to assess field loss at finer scale and aggregate the yield at regional or larger scale. These type of informations are relevant to policy-makers to provide guidelines for market intervention, trade and assistance.

Advances in Information Technology (IT) has provided the way to agricultural management. Processing of remotely sensed multispectral data, calculation of different reflectance indices, crop cover identification, disease identification & spread modeling, weather monitoring and forecasting, decision support systems and yield estimation are some of the techniques which are based on IT (Weiss, Jacob et al. 2020). Crop yield estimation is usually performed using various methods and data sources such as expert knowledge, field surveys, statistical modeling and crop growth simulation models (Weiss, Jacob et al. 2020). Identification of crop condition and its potential outcomes can provide useful insights which can be helpful to cater the yield loss (Dutta 2006). Various crop growth monitoring and yield estimation models are developed by research community which are based on soil, weather and remotely sensed data (Matthews and Stephens 1998, Matthews, Stephens et al. 2002, Stephens 2002). Pre-harvest yield estimation therefore plays an important role in maintenance of national food security (Hayes and Decker 1996).

Tea (Camellia sinensis) is a high value crop and among biggest commodity of Pakistan (Waheed, Hasid et al. 2002, Hamid 2007). Pakistan spends large revenue on import of tea and any development in its yield improvement may be beneficial for economy (Hamid 2007). We have started our work in collaboration with National Tea and High Value Crops Research Institute (NTHRI), Shinkiyari, Mansehra. It is an evergreen shrub and its leaves are plucked to produce green tea, black tea or oolong tea (depends on processing). Its tree is cut to below two meters when cultivated for tea production. Different leaf ages provides different quality of tea depending on their chemical foot print, usually small and fresh leaves are plucked for tea every once or two weeks. Tea was originated in Southeast Asia and is cultivated in warm-wet summers and cold-dry winters. The tea plants require annual rainfall with the range of 1150 to 1400 but its distribution throughout the year is equally important. Humidity also has a good relationship with tea yield and the quality of produced tea. A relative humidity of above 90% and temperature range of 20-26C is very helpful for high yield and good quality. Soil PH is a very good indicator of yield prediction as it is affected with land fertility, land humidity and plant growth because temperature, rainfall and humidity are directly related to this parameter. Temperature at the other had is a very critical parameter as the significantly low or high temperature may entirely stop the growth regardless of other parameters. In the case of Tea farms at Shinkiyari, temperature usually remains in favorable range and doesn’t cause catastrophic effect on the growth. Sunshine, fast wind and hail affects the growth as well but in the current data, we don’t have access to this information. Laycock et al. (Laycock 1964) in his classical review stated that the ideal growing weather for tea is warmer temperature with high humidity and sunshine in the day and adequate rainfall during night time. In this study, parametric analysis is performed to identify the important parameters and irrelevant or redundant parameters are eliminated. Feature Selection is performed using a hybrid approach which perform feature ranking with ReliefF algorithm and sequentially add these ranked features until model performance stops increasing. These selected and complete feature sets are used to train on different regression algorithms to set a baseline performance as the dataset under use is not previously evaluated by researchers. The final model is constructed by training proposed neural network ensemble on the processed feature set.

2 MATERIALS

The data used in the study is gathered from the farms in Shinkiyari, District Mansehra (latitude, 34°27’ E; longitude, 73°16’ N; altitude, 542m) which are operated by NTHRI of Pakistan. The data is collected on monthly basis and obtained from year 2008 to 2018, a total of 120 samples. The data contains nine independent variables namely minimum and maximum temperature of the farm, humidity level, rainfall, PH value of soil, per labor cost, labor training level, pesticide use, month and yield. Labor cost is not used in model design as it has no direct effect
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on yield and its values increased with time. Labor training levels has only two different levels and has shown no correlation with the yield. Similarly, pesticide use is also excluded from model design as it only mention that pesticide is used and there is no mention of its amount or type. Minimum and maximum temperatures are extracted from daily temperature readings recorded in the farms and their maximum and minimum values within a month are recorded. Humidity is the level of humidity recorded within the farms on daily basis and their average value during a month is recorded. Rainfall is the total amount of rain during a month. PH level is the average value of PH which is measured at a depth of 0.3m at various sites in the tea farm. Month refers to the categorical variable corresponding to each month of the year and it was found to have good correlation with the yield. Yield is recorded value of crop produce in kilograms for black tea.

Uncertainty in the recorded parameters arise due to spatial variability of weather and soil parameters i.e. soil PH and temperature are taken at some fixed points and their values is usually averaged for a month’s period. Average temperature is calculated for each month from minimum and maximum temperature value as it may better represent the yield and incorporated as another variable.

Table 1 Inter-Parameter Pearson correlation coefficient test.

|       | Avg. Temp | Max Temp | Min Temp | Humidity | Rainfall | PH Scale |
|-------|-----------|----------|----------|----------|----------|----------|
| Avg. Temp | 1.000     | 0.967    | 0.969    | 0.132    | 0.248    | 0.048    |
| Max Temp  | 0.967     | 1.000    | 0.875    | -0.010   | 0.119    | 0.147    |
| Min Temp  | 0.969     | 0.875    | 1.000    | 0.261    | 0.358    | -0.052   |
| Humidity  | 0.132     | -0.010   | 0.261    | 1.000    | 0.354    | -0.241   |
| Rainfall  | 0.248     | 0.119    | 0.358    | 0.354    | 1.000    | -0.630   |
| PH Scale  | 0.048     | 0.147    | -0.052   | -0.241   | -0.630   | 1.000    |

Table 1 provide the values of Pearson correlation coefficient test between different parameters. These test measures the linear relationship of a variable with others. It is notable that average, maximum and minimum temperatures has very high correlation with each other. The reason for this relation is that three of these temperature values varies in a linear relationship to each other’s. Some variables have negative linear relationship with each other and indicates that increase in one will result in decrease in the other variable such as rainfall will result in decreased PH level.

Table 2 linear correlation between dependent variables and independent variable

|       | Avg. Temp | Max Temp | Min. Temp | Rainfall | Humidity | Soil PH |
|-------|-----------|----------|-----------|----------|----------|---------|
| Correlation with Yield | 0.35 | 0.22 | 0.47 | 0.87 | 0.38 | -0.74 |

Table 2 provides the values of Pearson correlation between the independent variables and yield. It can be noted that all the independent variables have positive correlation with yield except soil PH. Moreover, rainfall has the highest value of correlation coefficient with yield. It could be noted that PH value is negatively correlated with rainfall and have highest inter variable correlation.

As a final feature set we have eight parameters (features) as an independent variables and one parameter, yield, as dependent parameter.

3 METHODS

Crop yield forecasting is done by fitting regression algorithm on the available data and testing on unseen samples. We have tried nine different regression algorithms on the available data and performed cross-validation to find the most suitable one for our scenario. Following are the steps followed to construct the crop yield forecasting model.

3.1 Outlier Analysis

Outliers are the samples which have strong influence on the model’s performance. These points may be erroneous measurements and cause the model to behave improperly. Outlier analysis is performed to identify the influence points and check them for their validity. Identified outliers are sometimes removed or they are replaced through smoothing. We have used Cook’s distance to identify the influence points. We have selected those points with
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Cook’s distance larger than 0.5 to treat them as outliers and they are provided in Table 3. Sample ID indicate the index of the outlier sample, yield is the value of yield for the outlier and the last one is Cook’s distance which is the basis of their selection. The performance of the model before and after the removal of outliers is provided in results section.

| Tuple ID | Yield       | Cook’s Distance |
|----------|-------------|-----------------|
| 84       | 115.8345469 | 0.76            |
| 56       | 44.76559721 | 0.58            |
| 60       | 71.6392121  | 0.50            |

3.2 Feature Scaling

Feature scaling is a fundamental step for a lot of machine learning problems due to a lot of reasons. It involves scaling the range of features to a specified range as different features are measured in different units and may have large variation in their range. The need of feature scaling arise as different ranges of features may cause the objective function to work improperly. It is especially important for distance based algorithms as when the features have different ranges, distance measure will be governed by the feature with large range. It is therefore preferred to normalize the range of all the features so that each feature contribute almost proportionately towards distance measure. In gradient descent and stochastic gradient descent, the convergence speed is sometimes improved after application of feature normalization (Grus 2015, Ioffe and Szegedy 2015). In SVM, feature scaling can reduce the time to find support vectors and affect the results as well (Juszczak, Tax et al. 2002).

There are different approaches to feature scaling such as min-max scaling, mean normalization, scaling to unit length and standardization. We have used standardization due to its advantages in neural networks, SVM, perceptron and radial basis function (Grus 2015). The standardization is performed so that data has zero-mean and unit variance and is calculated with the below formula:

\[ x' = \frac{x - \bar{x}}{\sigma} \]  

(1)

3.3 Feature Selection

More number of features can help the model in performing the predictions but irrelevant or redundant features can confuse the prediction algorithm or may cause unnecessary computational complexity. Irrelevant features are the parameters which has no correlation with the yield and the redundant parameters are those who have high correlation with each other’s and one of them can serve the purpose of the other. Feature selection therefore, makes the model simpler, reduce computational complexity, avoid curse of dimensionality and may increase the prediction accuracy by reducing overfitting.

There are numerous approaches to features selection with their advantages and limitations. We have opted a hybrid approach which use ReliefF (Robnik-Šikonja and Kononenko 2003) and sequential feature selection (Aha and Bankert 1996). ReliefF algorithm works by penalizing the features which give different values to the neighbors of the same class and reward the features which give different values to the neighbors of the different classes. The algorithm provides the rank of each feature and weight associated to each one of them. Normally the features with positive weights are the ones which provide good prediction and the features with negative weights are the ones which negatively affect the prediction. Figure 1 provides the ranked features on x-axes and their weight value on the y-axes. It can be noted from the plot that only three features have positive values and the rest of the features have negative values. We applied forward feature selection approach by sequentially adding each features in the ranked order and cross-validating it for reduction in Root Mean Squared Error (RMSE).
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We selected linear SVM for cross-validation evaluation of features and selected five features. A RMSE value of 6.1999 was achieved using linear SVM with five features as provided in Table 4.

3.4 Feature Transformation

Feature transformation sometime help in improvement of model performance. One purpose of using feature transformation is to compress the dynamic range of data which is useful in many algorithms. We have tried square root, reciprocal and log transformation on the data and checked the cross-validation performance. The log-transformation came out to be the winner of the three and have major effect on the distribution shape of the data. It is demonstrated to reduce the skewness and is appropriate for measured variables. It can’t be applied for zero or negative values.

3.5 Baseline Performance

Design of any prediction system requires an algorithm which is trained and validated on the dataset. Selection of a suitable regression algorithm is therefore fundamental to efficient model construction. Moreover, the dataset under use is not used for yield forecasting in past and need a baseline performance. To establish a baseline performance, we have trained seven different regression algorithms 10-fold Cross-Validation split. The four algorithms used for baseline performance assessment are Multiple Linear Regression (MLR), Support Vector Machines Regression (SVR) with linear and quadratic kernels, Gaussian Process Regression (GPR), Artificial Neural Networks (ANN), Random Forest (RF) and AdaBoost. The performance of these algorithms is computed on same CV split and performed on raw dataset and processed features for comparison.

3.6 Neural Networks Ensemble

The baseline results indicate that the GPR has minimum RMSE after hyperparameter optimization. We on the other hand want to opt neural networks ensemble due to some of its interesting properties. Ensemble learning is a very appealing topic due to its incredible simplicity and complex underlying dynamics. Neural networks are good at learning complex relationships between independent and target variables but suffer from instability. Multiple training instances of a single neural networks will provide different validation accuracy due to different convergence point of neural networks. An averaging ensemble can be simply used to average the prediction of multiple trained neural networks which will provide stable results and having good generalization. However, we can do more to improve the performance of neural networks ensemble.

To train a neural network ensemble we have constructed a shallow neural network architecture with only one hidden layer having five to thirty neurons in the hidden layer. The number of neurons in the hidden layer are randomly selected for each base learner. The training is performed by providing random subsampling of training data. It is to be noted that validation data is never used in any of the model construction phase, it is only used for
validation after the end of ensemble learning process. The training process has trained 100 base learners with random subsampling and varying architectures to introduce diversity in the models. Moreover, the trained base learners are combined on the basis of model selection approach to form ensemble.

3.7 Model Selection

It is better to combine few accurate base learners rather than combining all the base learners. Dietterich et al. (Dietterich 2000) has demonstrated that the base learners used for ensemble construction should be diverse and relatively accurate to make it effective. However, it is unlikely for both requirements to be true as if they are accurate they will be relatively similar (Christensen 2003). We have initially trained 100 base learners having architectural and training diversity and then few accurate one are added in the final ensemble. Wrapper based methods can be used to add models in the final ensemble by sequentially adding ensemble and cross-validating on a portion of dataset but we have opted a hybrid approach for model selection. The base models are ranked using ReliefF algorithm which provides feature weights and their rank. Figure 2 shows a bar chart of ranked base learners with their weights. The negative weights are assigned to the predictors conversely affecting the output. We have started sequentially adding base learners into the final model until there is no increase in the performance. Twenty four base learners are sequentially added into final model until there was increase in the performance and further addition of base learners provided no change in predictive performance.

![Fig. 2 Bar chart of ranked base learners with their assigned weights](image)

3.8 Output Calculation

The twenty four base learners sequentially obtained in model selection process are used for output calculation. We have calculated the output function by initially assigning higher weight to the learners with low mean squared error $E_i$. Weights are calculated for these predictors using a convex function to assign lower weight to a neural network with higher error and higher weight to a neural network with lower error. The weight $\omega_i$ of $i$th weak learner can be calculated using formula of equation 1.

$$\omega_i = \frac{1}{e^{-b(|E_i| - c)}}$$ (2)
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The final output of predicted value is calculated by weighted average of 24 base learners which is given by the formula of equation 3.

\[ Y_{pred} = \sum_{i=1}^{10} \omega_i \times Y_i \] (3)

The flow chart of the proposed ensemble learning process is provided in Fig. 3.

4 RESULTS AND DISCUSSIONS

Linear models are very powerful tool in modeling different systems and their performance depends on the nature of input and target parameter’s linearity. Non-linearity of parameters may lead to poor performance and can be catered by selecting the linear parameters only or transforming them to form a linear relationship. In our scenario, we have tried to reduce non-linearity by transforming some parameters.

Table 1 provides the values of independent variables and target variables. It is evident that rainfall demonstrates best linear relationship. PH also has somewhat linear relationship but temperature and humidity parameters have poor linear relation. PH is observed to be highly impactful variable in determining the tea yield followed by rainfall, month of the year, temperature and humidity. Moreover, PH Scale has the highest correlation with tea yield. It is indicated PH scale has negative relationship with yield whereas the other parameters such as rainfall, average temperature, humidity has positive linear relationship based on calculated coefficients. It is evident that it’s difficult to map the data by using linear model but we have adopted a modular approach and found the cross-validation accuracy at each stage.

In first stage we discarded the features which have no relationship with the target variables based on empirical analysis such as labor cost, labor training, pesticide and year of harvest as some of them have consistent values. After that feature selection is performed by first ranking them with ReliefF algorithm and then applying sequential feature selection to add each ranked feature one by one to get the best feature set. The selected feature set contained five features. Table 4 provides the improvement in the results after feature selection stage.
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Table 4 RMSE of five regression models after each stage

| Model      | Raw Dataset | Feature Selection | Feature Scaling | Outliers Removal | Feature Transformation |
|------------|-------------|-------------------|-----------------|-----------------|-----------------------|
| GPR        | 7.1456      | 6.6265            | 6.3128          | 5.9961          | 0.1542                |
| Linear SVR | 8.1314      | 7.9937            | 7.8867          | 7.778           | 0.2215                |
| Quadratic SVR | 7.4107   | 7.3067            | 7.1077          | 6.4612          | 0.1696                |
| MLR        | 8.2140      | 7.9148            | 7.4444          | 7.4328          | 0.2151                |
| ANN        | 7.1954      | 6.8541            | 6.2724          | 5.9614          | 0.1674                |
| RF         | 7.1871      | 6.9821            | 6.4215          | 5.9712          | 0.1705                |
| AdaBoost   | 7.4831      | 7.1421            | 6.8725          | 6.2143          | 0.2024                |

The next stages were feature selection and outlier removal which provided subsequent reduction in RMSE. The last stage was feature transformation which provided significant reduction in RMSE. The RMSE value for ANN varies significantly after retraining and therefore five iterations at each stage were conducted and the average of these five iterations is recorded in the table.

The results of Table 4 indicate the lowest RMSE value is provided by GPR with exponential kernel. The results of SVR with linear kernel and multiple linear regression are consistently low which is due to non-linear nature of the problem set. The three non-linear methods have provided lowest RMSE out of which GPR has a value 0.1542, quadratic SVR has a value of 0.1696 and ANN has an average value of 0.1674. The three non-linear methods have provided lowest RMSE out of which GPR has a value 0.1542, quadratic SVR has a value of 0.1696 and ANN has an average value of 0.1674. The three regression algorithms with lowest RMSE are evaluated to choose the final model.

The evaluation to select final model is performed by randomly splitting the data into 20% (28 samples) for testing and 80% (113 samples) for training. This splitting is performed so that each model gets the same data for training and testing.

The SVR with quadratic kernel is tuned by optimizing its hyper-parameters. Figure 3 provides the minimum objective vs the number of function evaluations and the selected hyper-parameters for estimated objective function value of 0.045452 are provided in Table 5.

Table 5 Optimized hyper-parameters for quadratic SVR

| Box Constraint | Kernel Scale | Epsilon   |
|----------------|--------------|-----------|
| 5.375          | 8.5463       | 0.093389  |

Fig. 4 Minimum objective vs the number of function evaluations for SVR with quadratic kernel
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The GPR with squared Exponential kernel is tuned by optimizing its hyper-parameters. Figure 4 provides the minimum objective vs the number of function evaluations for GPR and the selected hyper-parameter value for sigma is 0.16517 at estimated objective function value of 0.034994. Figure 5 provides objective function model with 95% confidence interval.

![Minimum objective vs the number of function evaluations GPR](image)

**Fig. 5** Minimum objective vs the number of function evaluations GPR

![Estimated values of objective function for different values of sigma](image)

**Fig. 6** Estimated values of objective function for different values of sigma

| Table 6 Performance parameters of three models |
|----------------|-----------|---------|---------|-----------|
|                | SVR       | GPR     | ANN     | RF        | Proposed  |
| MAE            | 0.1763    | 0.1328  | 0.1795  | 0.1426    | 0.0942    |
| MSE            | 0.0039    | 0.0034  | 0.0300  | 0.0353    | 0.0145    |
| RMSE           | 0.0626    | 0.0581  | 0.1732  | 0.1705    | 0.1204    |
| $R^2$          | 0.8357    | 0.9078  | 0.9213  | 0.8942    | 0.9461    |

Table 6 provides the performance parameters for the three algorithms. The performance is compared based on four evaluation measures among which are MAE, MSE, RMSE and coefficient of determination $R^2$. ANN gave
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best R2 but it is not stable and the values of MSE and R2 varied a lot with several iteration having same training and test data and different initial conditions. The variance in ANN model is reduced by using ensemble of neural networks. GPR and SVR on the other hand are stable as their performance only vary slightly with change in training and test data. The GPR provided best single learner performance whereas the ensembling of neural networks has beaten its performance and provided even higher performance. The proposed model provided highest value of coefficient of determination indicating that the proposed approach has best prediction performance in comparison to baseline approaches. The proposed approach has provided a MAE of 0.0942, MSE of 0.0145, RMSE of 0.1204 and R-squared of 0.9461.

The study highlight that neural networks ensemble have shown best generalization performance. ANN are known to model the complex relationships between independent and dependent variables and their variance can be easily managed by ensemble learning which provide stable models. It is also highlighted that selection of some good performing neural networks is better than adding all the base learners. The selected base learners can be added linearly, through weighted averaging or convex function approach. Moreover, the weights assigned to base learners using ReliefF algorithm were also used to calculate the final weighting function but weight assignment using proposed approach has provided best performance.

Tea is mostly cultivated on smaller farms with hilly terrain and use of remote sensed data (reflectance indices) could only be possible if a finer resolution imagery is available. Availability of such imagery is expensive and difficult for small or medium scale farmers so a surface parameters based model is more suitable approach which has provided reasonable performance. Moreover, the hilly terrain provides shadow effect and the tea cultivation area in Pakistan have high cloud cover rate so there are additional challenges associated with the use of remotely sensed imagery. Moreover, performance of surface parameters based model has shown promising results and it indicates its utility in tea and other high value crops.

1. CONCLUSION

The present study has demonstrated the use of different methods for crop yield forecasting of tea plant. Linear regression models are simplest regression approach as they have low variance but the parametric analysis indicated that predictor and response relationship is not linear and a non-linear approach would be more suitable for the problem. To solve the problem data pre-processing methods are extensively explored and described. Five regression algorithms are applied to fit the model among which two are multiple linear regression and support vector machines regression with linear kernel are the two linear algorithms. Support vector machines regression with quadratic kernel, Gaussian process regression with exponential kernel and artificial neural network are the non-linear algorithms. RMSE with 10-fold cross-validation of linear algorithms was quite high so the non-linear algorithms were carried on for further analysis. Fine tuning of these algorithms is performed and their performance is measured on four evaluation metrics. ANN provided the highest values for MAE, MSE and RMSE indicating its poor performance but it provided best result for coefficient of determination (R2). On the other hand, GPR provided lowest values for MAE, MSE and RMSE and the value of R2 is slightly low then ANN. Moreover, the value of ANN varies a lot with retraining of the model with same training and testing data showing instability so the proposed boosting method utilizing the ANN as weak learner provided relatively stable performance with MAE of 0.0942, MSE of 0.0145, RMSE of 0.1204 and R2 of 0.9461. The evaluation is performed using 30% hold-out data which is not used in training or validation and it indicates good generalization indicating that the model can be successfully deployed for yield forecasting of tea or other high value crops.

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