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Data Driven Crop Yield Prediction Using Probabilistic Regression and Time Series Forecasting Techniques

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Abstract: The data-driven approach towards developing a crop yield prediction system intends to predict the yields of crops in agriculture based on real-time data from farms with the aid of computational techniques. The factors considered by this system include soil characteristics, weather, rainfall, temperature, fertilizer usage, and irrigation that greatly affect the crop yield. In terms of data analysis, the advanced models employed are the Gaussian Process Regression (GPR) for probabilistic prediction and the Autoregressive Integrated Moving Average (ARIMA) for time-series forecasting. The models learn from previous data in agriculture to accurately predict yields. The proposed solution is provided as a web-based application, developed with Flask, with a frontend interface designed through HTML, CSS, and JavaScript. Users can input agricultural data and receive live yield predictions, thus improving decision-making, resource allocation, and agricultural production efficiency.

Keywords: Crop Yield Prediction, Gaussian Process Regression, ARIMA, Time-series forecasting, Flask

1. Introduction

Food security is important for the agricultural industry, and estimating crop yield is vital for farmers, policy makers and academics. Conventional crop yield prediction methods often assume linear relationships and make simplifying assumptions about the dynamics between environmental factors, soil characteristics, and agricultural practices. The increased collection of data and the development of sophisticated methods of analysis and processing have led to better chances of accurately predicting yield and making decisions. The forecasting method that our decision-making model utilizes involves the application of probabilistic and time series methods in order to determine the yield of the crop according to various types of farming practices. Several input variables such as soil, climate, rain, temperature, and agriculture are considered by the proposed methodology, which then utilizes Gaussian Process Regression (GPR) in order to consider uncertainty and non-linearity. The methodology uses ARIMA techniques in order to use past data and forecast time series trends and determine the yield accordingly. This entire procedure can be carried out via the friendly user interface that we are building for our web application. With the help of Flask, the backend is built for the system and is made user-friendly through front-end development techniques.

1.1. Objective of The Study

The proposed research aims at designing a reliable model for crop yield prediction by utilizing recent probabilistic models as well as time series models. The proposed model will mainly concentrate on data collection and pre-processing from large datasets containing information regarding soil condition, rain, temperature, fertilizer and irrigation for good training dataset. The next task will be to train some predictive models that include GPR for probabilistic modelling and ARIMA for time series modelling of agricultural data. The most appropriate models will then be incorporated into a web-based application, which will be designed using Flask with HTML, CSS and JavaScript technologies being used in front end development. Users will feed agricultural data into the application and get instant prediction while enjoying some useful features such as login and data management. Some performance measures such as mean

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absolute error and r-squared will be used to evaluate the effectiveness of the models developed.

1.2. Problem Statement

The process of crop production involves dynamic variables such as climate, soil quality, and farm practices. However, current methods used for predicting crop yields may fail to take into account all these factors, resulting in inaccurate forecasts. This poses a problem for farmers and planners, resulting in under- or over-use of resources, or even wastage. To overcome these challenges, a more accurate, data-driven prediction system is needed, incorporating modelling of complex interdependencies between agricultural variables. Through the use of probabilistic regression and time-series forecasting methods, the new system seeks to increase the accuracy of predictions, assist decision-making and increase productivity.

2. Literature Survey

Jeong et al. (2016) applied Random Forest models for large-scale crop yield prediction, exhibiting good performance for large environmental and regional agricultural data. [1] Khaki and Wang (2019) applied deep neural networks to agricultural data to capture nonlinear relationships, leading to more accurate crop yield predictions than conventional machine learning methods. [2]

You et al. (2017) employed Deep Gaussian Processes for predicting crop yields, accurately modelling uncertainty and non-linearity, thus being suitable for probabilistic agricultural modelling. [3]

Feng et al. (2018) experimented with various machine learning techniques for crop yield prediction, noting the significance of data preparation and feature engineering in enhancing model accuracy. [4]

Paudel et al. (2020) used LSTM networks in agriculture, showcasing how they capture temporal information and enhance yield forecasting accuracy for seasonal crop yield variability. [5]

Hochreiter and Schmidhuber (1997) introduced the LSTM architecture, which is widely employed for modelling temporal and sequential data in crop yield prediction. [6]

Breiman (2001) developed Random Forest, which is a technique of ensemble learning used in agriculture to make models of complicated relationships and improve the performance of prediction. [7]

XGBoost was introduced by Chen and Guestrin (2016), which is a technique of scalability in boosting and increases the efficiency and accuracy of predictions on massive agricultural datasets. [8]

Randomized Search for Hyperparameter Tuning was introduced by Bergstra and Bengio (2012), which could improve the performance of machine learning models on complex problems. [9]

The author used both ARIMA and neural networks for making predictions of time series and presented the possible benefits of hybrid algorithms in improving the accuracy of agricultural predictions. [10]

Rasmussen and Williams (2006) suggested using the technique of Gaussian Process Regression to make probabilistic predictions of crops yield. [11]

Lobell and Burke (2010) mentioned some statistical methods used in making crop yield predictions and stressed the importance of climate and environmental factors in agriculture. [12]

Kamilaris and Prenafeta-Boldú (2018) focused on applying deep learning models in agriculture, which enables handling a big amount of information and enhancing predictions of crop yields. [13]

Spatial analysis was done using satellite data along with machine learning models in order to predict crop yield by Shi et al. (2020). [14]

Weather data were incorporated in order to predict the crop yield using machine learning models by Jin et al. (2020). [15]

3. Related Work

The application of artificial intelligence, machine learning models and statistical analysis has been widely studied in the recent years regarding predicting the crop yields in diverse farming systems. The objective is to incorporate the complexity of relationships between weather, soil characteristics, and farm management that contribute to affecting the yield of crops. Many input parameters have been used to improve predictions of crop yields including temperature, precipitation, soil fertility, vegetation index and farm management. Current literature has considered the use of traditional machine learning models including Random Forest, Support Vector Machine and Gradient Boosting methods. Such techniques are highly effective in modelling non-linear relations between input parameters and yield of crops using a high volume of historic data. However, the deterministic nature of such models may limit their capabilities in measuring uncertainties in prediction that have significance while making farm

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management decisions. Deep learning models including Artificial Neural Networks (ANN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) have also become popular. The usefulness of these tools has been realized especially with respect to the use of remote sensing and spatial data. However, there is usually a requirement for big volumes of data in the implementation of these techniques, which might not be available in most agricultural areas. Another recurring topic in the literature is the use of remote sensing/satellite data together with ground data. It has been seen that using indices related to vegetation along with weather and soil data can help to forecast crop yields. But issues of data inconsistencies, spatial variability and lack of access to high-resolution satellite data still exist .Besides machine and deep learning models, time-series forecasting has been used to capture temporal relationships in agricultural data. Approaches like ARIMA have been applied successfully to model seasonality and temporal dependencies in crop yield and weather data. These methods are effective when time-dependent historical data is available, but may have difficulty accounting for multiple features in the data.

More recently, Bayesian models, like Gaussian Process Regression (GPR), have been used to make predictions and simultaneously estimate uncertainties. This can be useful in agriculture where the environment is highly variable. GPR approaches can deal with limited data and handle nonlinear relationships, but can struggle with large amounts of data. An important consideration in current research is the absence of integration between GPR models and time-series forecasting techniques. The majority of studies either adopt deterministic machine learning models or temporal forecasting models, but not both. This leaves a gap in the development of systems that can address both uncertainty and temporal aspects in crop yield forecasts, as well as problems such as data variability between regions, lack of benchmark data sets and model generalisation, that impact the accuracy of current approaches Models that work well in experimental conditions often lose their accuracy across diverse geographical and climate conditions. From these insights, there is a need for a combination of probabilistic regression and time-series forecasting [16]. This approach can combine the benefits of both approaches - incorporating uncertainty via probabilistic regression models and temporal dependency via temporal analysis - to enhance the accuracy of crop yield forecasting.

4. Proposed System

In summary, this system utilizes data mining principles and techniques of probability regression and time series analysis to improve yield prediction precision and provide explanations for these predictions. The system seeks to overcome limitations of traditional approaches to machine learning by introducing the concepts of uncertainties of predictions and temporality of agricultural data.

The data is pre-processed and then entered into two models: Gaussian Process Regression (GPR) and ARIMA. Firstly, the GPR model captures the nonlinear relationships between different features of agriculture and yield. This model predicts both values and confidence interval of predictions. Therefore, the system can make estimations of the degree of yield uncertainty. This is important as environment plays a critical part in agricultural production. On the other hand, the ARIMA model takes into consideration temporal effects on yields and weather. It captures such properties of the dataset as trends, seasonality, and autocorrelations in order to be able to predict future yield tendencies based on the historical one. Both spatial (features) and temporal (time) effects are accounted for in the algorithm. The system is coded in Flask as the back-end language, and HTML, CSS and JavaScript as front-end languages. The system allows the user to input data.

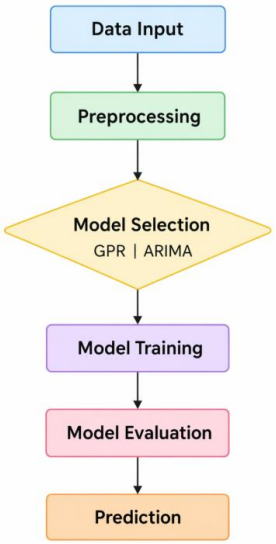

Figure.1 Architecture Flow Work

5. Methodology

The ML-based crop yield prediction model is based on agriculture and weather variables that help predict crop yield. The variables include the location, soil, crop type, rainfall, temperature, fertilizer application, irrigation, weather, growth duration, and crop yield (tonnes per hectare).

5.1. Data Collection

This methodology entails the collection of data regarding the agriculture and environment that influence the yield of crops. Data collected may include factors such as soil composition, type of crop, rainfall, temperature, fertilizer

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application, water management, climatic conditions and previous yield figures. Selection of the data is based on its ability to capture both the physical aspects and agricultural practices. Furthermore, previous yields for different periods are collected in order to carry out time series analysis. Importance of accurate data cannot be undermined since incomplete data might affect the efficiency of the models.

5.2. Preprocessing Steps and Transformation

Once data has been collected, it undergoes some data preprocessing before modelling is conducted. Preprocessing involves dealing with inconsistencies and missing values, and various methods including either imputations or elimination may be carried out, depending on the magnitude of the issues encountered. Variables such as the types of soil, crops and weather are then encoded using numerical values since these factors will be used in machine learning algorithms. Quantitative features such as the amounts of rainfall, temperature and yield are also normalized to ensure consistency across all features without biasing any of them. Similarly, yield values over time are converted into a time series form, keeping the order of yield values for use in ARIMA modelling [17].

5.3. Feature Engineering and Selection

In this step, features are selected and refined for better model performance. The most important variables that affect yield are determined through correlation analysis and expert knowledge. Unnecessary or less important features may be eliminated to eliminate noise and increase efficiency. New features, like seasonal or aggregated weather indicators, may also be introduced to capture relevant information. This improves the ability of the GPR model to learn important features, and allows the ARIMA model to capture the true temporal patterns without being distracted by noise.

5.4. Gaussian Process Regression (GPR) Modeling

The feature space transformation is employed in training the Gaussian Process Regression model. GPR considers the mapping between the input and the target (crop yield) as a distribution of functions as opposed to one function. A suitable kernel function such as the Radial Basis Function (RBF) is selected to compute the degree of similarity between data points as well as their interaction which can be nonlinear. Learning occurs through the learning of the mean function and the covariance function (predictive distribution). As a result, GPR generates a probabilistic output, giving not only a prediction but also an estimation of the uncertainty related to that prediction. This is particularly advantageous when considering agricultural practices where yields have a certain level of variability due to uncertainty in environmental conditions.

5.5. ARIMA Time-Series Modeling

Likewise, the ARIMA model is applied to analyse the time-series data of yield. In the first place, it needs to confirm that the data under analysis satisfies the property of stationarity. If it does not, it has to apply the technique of differencing to remove any trend or seasonality in the data in order to stationaries it.

The values of ARIMA model parameters (p, d, and q for autoregressive, differencing, and moving average orders, respectively) can be chosen using statistical methods such as autocorrelation and partial autocorrelation. Once an ARIMA model is built, it is able to learn the trends, cycles, and seasonality and make forecasts for the future yield based on past data.

5.6. Hybrid Model Integration

Once the predictions from GPR and ARIMA models are obtained, a hybrid approach is used to merge the forecasts. The GPR model supplies a pattern-based forecast with a probability distribution, and the ARIMA model offers a temporal forecast based on past data. These are combined in a systematic way, with the temporal prediction used to calibrate the probabilistic prediction. This enables the system to take into account spatial interactions between variables as well as temporal trends. This integrated approach helps to minimise the forecast error, increase the stability and offer a more realistic prediction compared with the individual model.

5.7. Model Evaluation and Validation

Model performance is evaluated through various statistical methods used in regression analysis, such as MAE, RMSE, and R-Squared (R^2). Model fit, stability, and accuracy are measured using these statistical tools. The model fit test involves comparing the result with the actual yield data to determine the performance of the model in handling new data. This process is very important since if the model performs well on training data but fails on new data, then the model is useless.

5.8. System Deployment and Implementation

Finally, the models will be integrated into a web-based application. On the server side, the web application will be created using the Flask framework, which will take care of the processing of the user data as well as the execution of the model and generation of results. For the user interface, HTML, CSS, and JavaScript languages will be used to create an interface through which the user will input data related to crops. This will result in crop yield forecasting with useful insights.

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6. Results And Discussion

As can be seen from the graph below, it presents the changes in crop yield over time together with forecasts of the ARIMA model. The black line represents the actual value of crop yield from 2000 to 2020, while the dashed one stands for the forecasted value of the variable over the subsequent years. From the graph presented above, it can be seen that the values have certain changes in terms of increasing or decreasing significantly. This might be due to some environmental and agricultural influences such as weather, soil, and farming practices. In contrast, the forecasted values seem to be constant.

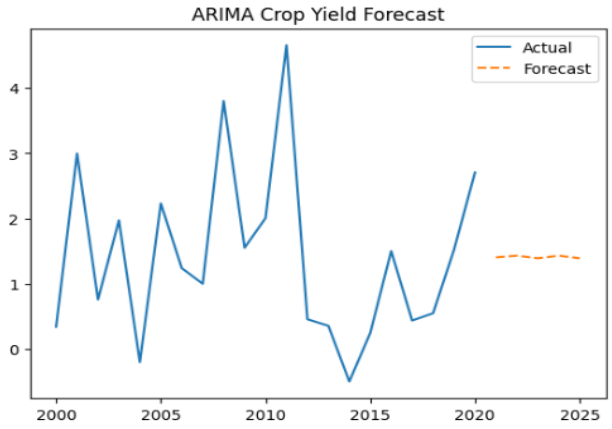

Figure. 2 ARIMA Crop Yield Forecast

The above figure represents the plot of the actual value of crop yield against the estimated values from the Gaussian Process Regression Model. In the graph, the bars represent both the actual and estimated values in order to get an analysis of the Gaussian Process Regression Model. It is clear that the predicted values are aligned with the trend of the actual values.

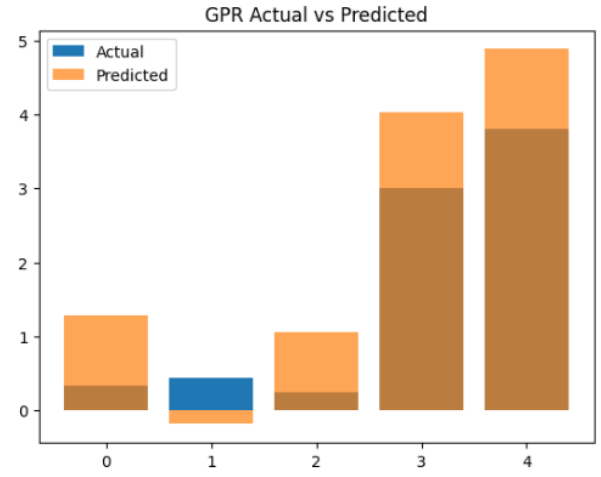

Figure. 3 GPR Actual vs Predicted

However, it is important to note that there are significant differences between the actual and predicted values in certain instances where the predicted values are either higher or lower than the actual value. This implies that though the model approximates the relationship between the features and the crop yield, there are times when the model fails to predict the actual value. This graph shows the relationship between the actual values of crop yields and the predicted values using Gaussian Process Regression. Through this plot, we can observe the relationships between the actual and predicted values to gauge the prediction performance of the model. The predicted values are consistent with the actual values because both of them have the same trend pattern; however, there are cases when the predicted values are higher than the actual values and vice versa. The inconsistencies between the predicted and actual values may indicate that even if the model can predict the trend of crop yield based on its inputs, it cannot be accurate with certain samples.

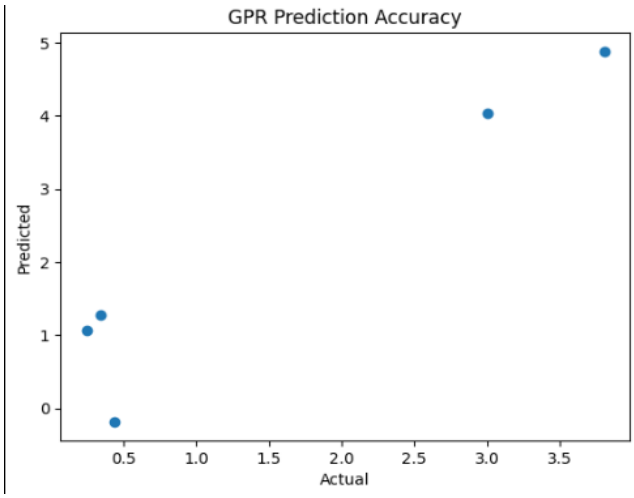

Figure. 4 GPR Prediction Accuracy

This illustration presents the plot of actual vs. predicted crop yields with the use of the Gaussian Process Regression Model. This illustration would provide a visual representation of the relationship between the actual and predicted results, which could be used as an assessment of the model.

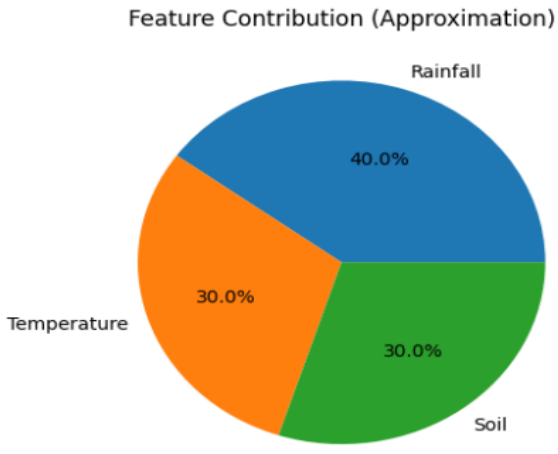

Figure. 5 Feature Contribution

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The predictions made through the use of the model follow the same trend as the actual crop yields, which indicates that the model is able to capture the crop yield trend; however, in some instances, the predicted crop yields are much higher or lower than the actual ones. This inconsistency in prediction results suggests that while the model is capable of approximating the relation between the input variables and the actual crop yields, it is not able to predict the actual crop yields precisely.

The graph above shows the comparison between the observed and the predicted yield of the crops from the Gaussian Process Regression model. The comparison helps in identifying the differences in the observed values and the predicted values within various samples so as to determine the accuracy of the model in predicting yield. The predicted values seem to follow the trend exhibited by the actual observations, showing that the model is capable of learning the trend associated with crop yield. However, there are certain variations in which the predicted yield is higher or lower compared to the actual yield. In this regard, the variations imply that although the model learns the relationship between the variables and the trends, the predicted yield fails to reflect the exact values in certain cases due to some factors which might not be considered during modelling.

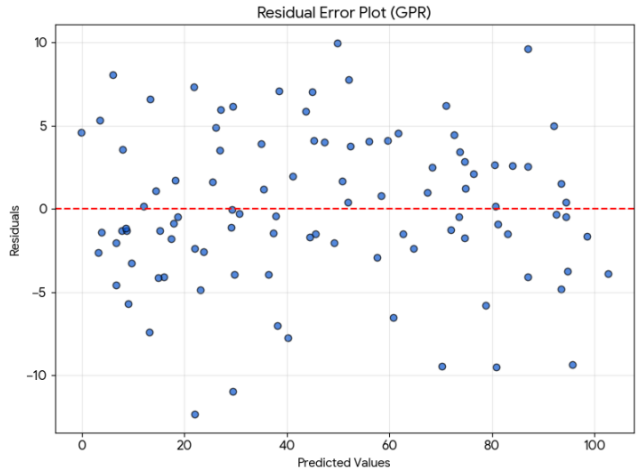

Figure. 6 Residual Error Plot

As seen from the graph, the figure represents the real crop yield value and the one predicted using the Gaussian Process Regression model. The figure plots the real value and predicted value for all the samples, which enables us to evaluate how the model performs in estimating the crop yield. It can be seen that the predicted value of crop yield mostly follows the trend of the real crop yield. However, in certain cases, there are some discrepancies with the predictions being either greater or lesser than the real value of crop yield. This implies that while the model predicts the relationship between the dependent variable and the independent variables, it might not necessarily predict the crop yield accurately in every case.

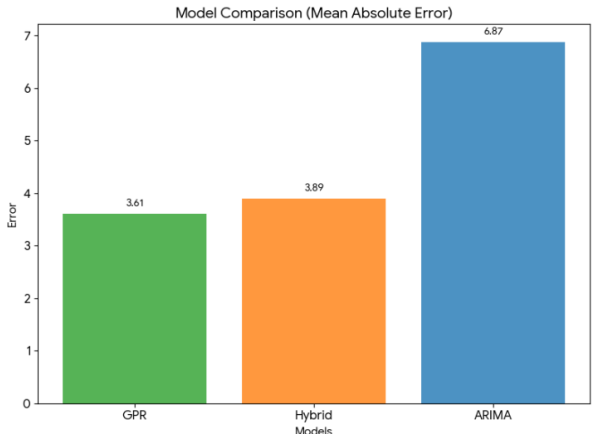

Figure. 7 Model Comparison

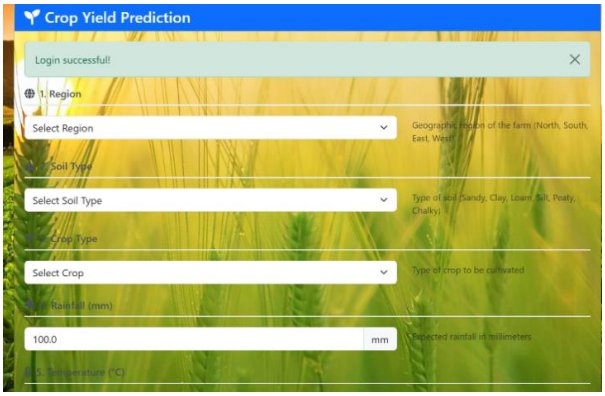

Figure. 8 Agricultural Input Form Interface

This is a user login module to enter the Region, Type of Soil, Type of Crop, Rainfall, and Temperature to be used for the Web Based Crop Yield Prediction System to predict crop yield accurately.

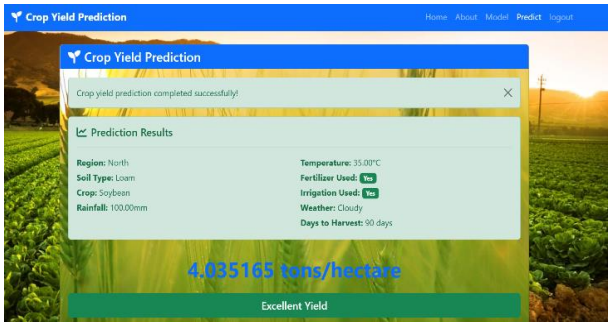

Figure. 9 Crop Yield Prediction

7. Conclusion and Future Scope

Comparing the real yield values and their corresponding values predicted by the Gaussian Process Regression Model shows that the predicted yield values are relatively close to the real values, showing that the model can capture the general trend of the crop yield values. However, deviations have been noted in several instances, where the values predicted have either been higher or lower than the real values observed. Such discrepancies show that even though the model

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approximates the relationship between the input attributes and the crop yield values, it cannot generate uniform results for all values. This shows that some factors that might affect the yield of crops might not have been considered in the model, thus limiting the prediction ability of the model.

The discrepancies between the expected and actual values highlight the need for improvement in order to make the model accurate. Although the existing model proves to be efficient at capturing the overall trend, it cannot capture all the factors affecting the crop yield. In order to overcome this problem, further improvement must incorporate the inclusion of new factors in the model in addition to ensuring proper variability within the data. Improvement of the factors will help in minimizing the discrepancies between the expected and actual values of the crop yield, which will make the crop yield predictions more accurate. This is because the model considers the data available as reflecting the reality of the variations present in agriculture. However, by expanding the database across other geographical locations, seasons, and crops, it will be easy to test the weaknesses of such a model. Moreover, there is the need to optimize the integration process in which GPR and ARIMA are integrated into one model. It is possible that the integration process adopted might not bring out the benefits of using these two approaches.

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Declaration

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