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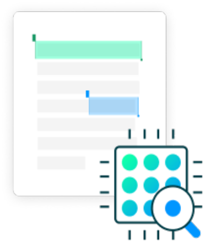

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National College of Ireland

A Hybrid Machine Learning Approach for Crop Classification, Yield and Fertilizer Prediction for Sustainable Agriculture

MSc Research Project
MSCDAD

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<u>QUESTION 1</u>: What are the key machine learning models used in agricultural prediction, and why did you choose SVR, XGBoost, and MLP for your study?

Machine learning has emerged as a cornerstone of modern agricultural prediction, offering powerful tools to analyze diverse and complex datasets. These models excel in yield forecasting, pest detection, and resource optimization, among other tasks, that are transforming agricultural decision-making. The Key models used include:

a) Ensemble Methods such as Random Forest (RF) and Gradient Boosting Machines (GBM) enhance the prediction accuracy by combining multiple models. RF builds a multitude of decision trees for handling both numerical and categorical data and thus, is appropriate for crop classification and soil analysis. GBM, on the other hand, decreases the error in a sequential manner and hence is appropriate for regression tasks like yield prediction.

b) Neural Networks and Deep Learning: Models in these categories perform very well in finding complex patterns in agriculture data. Some of the commonly used ones include:

   - Convolutional Neural Networks: These are designed for spatial data analysis. CNNs find wide applications in satellite imagery to monitor crop health, detect pests, and enable precision agriculture.
   - Long Short-Term Memory Networks-LSTMs: This is a form of RNN which learns from sequence dependencies found in time-series data, and that can be quite ideal for seasonal trend forecasting, and resource demands.

c) Support Vector Machines: SVM is useful for classification and regression problems where either the relationship between the data is complicated or the sample size is small.

d) Hybrid Models: The hybrid models combine the power of several approaches and integrate spatial, temporal, and other agricultural data for robust and comprehensive analysis.

These models lead the way in agricultural innovation, along with improvements in ensembling and deep learning, by allowing precise, data-driven insights into sustainable and efficient farming.

In this research, SVR, XGBoost, and MLP were chosen for the meta-model layer due to the following reasons:

- Support Vector Regressor is a kind of kernel-based method that can easily capture the nonlinear relationship in the data. Thus, it has robust predictions with less overfitting in smaller to medium-sized datasets. The inclusion of SVR was because it provides a good balance between complexity and accuracy, especially in regression tasks. Its ability to handle data variability makes it well-suited for agricultural prediction.
- XGBoost is the most well-known gradient-boosted decision tree algorithm; it is mainly appreciated for its speed, scalability, and handling huge datasets. It incorporates regularization techniques that enhance performance on regression tasks of yield and

fertilizer predictions. In this way, it can model complex nonlinear relationships and hence assures robust performance in precision agriculture.

- The Multi-Layer Perceptron which is also known as MLP is a feed-forward neural network that is capable of modeling even the most complicated and nonlinear patterns. The high-accuracy tasks such as the classification of crops and the prediction of fertilizers are well-suited to this method because of its structure and adaptability in multi-layers. Agricultural applications usually benefit from the efficiency of MLP because of its capacity to learn complex relationships.

These models further complement the basic models, that is, Random Forest, Gradient Boosting Regressor, and LSTM, using their outputs and incorporating them into a robust hybrid framework. Among the experimental results found in this paper, the highest accuracy in crop classification was that of the SVR meta-model and very good performance of XGBoost and MLP with high precision in regression tasks such as yield and fertilizer prediction.

QUESTION 2: What is a meta model in the context of your project?

In the context of this project, a meta-model is considered as a high-level model that combines the predictions of the base models in order to achieve higher overall accuracy and robustness. Instead of using raw data directly, the meta-model takes the output from base models like Random Forest, Gradient Boosting Regressor and LSTM, analyzes the pattern or relationship between these predictions, and develops refined predictions to feed into the final neural network layer. This last layer takes the output from the meta-model and give very optimized and accurate results for target tasks.

Each of the base models was used for a specific task: Random Forest for crop classification, as it can handle categorical and numerical data; GBR for yield prediction to reduce regression error; and LSTM for fertilizer prediction, which is good at handling sequential data. Then, the meta-models: (SVR, XGBoost, and MLP) learn how to aggregate their strengths while mitigating individual weaknesses by integrating these base model outputs.

This hierarchical architecture reduces biases and errors of individual base models. For example, if any base model shows poor performance on some patterns then the meta-model balances it out and improves the output by leveraging complementary strengths across the different models. This was able to enhance the crop classification and yield prediction tasks due to the incorporation of temporal insight from LSTM, classification strength of Random Forest, and regression strength of GBR.

The proposed integrated and scalable framework will ensure flexibility for any future agricultural tasks or datasets while it also provides the ability to adapt to the different evolving scenarios. This architecture will ensure not only superior predictive accuracy but also a long-lasting solution for a wide range of agricultural challenges

QUESTION 3: How do you predict the yield of the next year, do you use variables from the current year?

In This study predicts next year's yield using a combination of historical data and anticipated environmental and management inputs based on historical patterns. In this way, the models capture long-term trends and relationships to provide accurate and reliable predictions.

The process begins by using historical data to understand the patterns. Models were trained using past data on crops, rainfall, fertilizer use and the properties of the soil. These variables help the models to learn about the pattern that is forming and various factors that affect how well crops perform in a certain area over time. The temporal features of Crop Year and Season were also crucial to account for year-to-year variability which will also enable the model to spot and adapt to seasonality and changes.

The other key factors of prediction included the estimated variables. These variables including rainfall, temperature, humidity, and fertilizer application were not taken from the current year but estimated from historical averages and trends. In this way, models use a realistic set of inputs for the upcoming year and this is reflective of expected environmental and management conditions.

The Gradient Boosting Regressor was used as the base model in the machine learning framework for the prediction of yield. It was selected because it is very efficient in handling the complexity in relationships between data. Further refinement of outputs from the base model was performed through a meta-model, which in turn was optimized by the final neural network layer. In this layered architecture, strengths of various models are combined together for more accurate yield prediction.

The experimental results proved the reliability of this approach. For example, the overall best model (the Grid Search Optimized MLP meta-model) achieved an R^2 score of 0.9769 and a RMSE of 0.1628 while predicting yield, hence proving to be effective in capturing both long-term trends and projected variability.

In conclusion the prediction process does not use the current year's variables directly but is based on historical data and estimated trends. Through this method, the study gives the most accurate and reliable yield estimates for the next year.

QUESTION 4: Is there a formula relating the area to the yield?

Yes, there is a direct formula that relates area to yield, given by:

$$\text{Yield} = \frac{\text{Production}}{\text{Area}}$$

In this formula Yield is defined as a quantity of production per unit area usually measured in metric tons per hectare. Production in this context is the total quantity of crops harvested, while Area is the total land under cultivation.

$$\text{Yield} = \frac{100\,\text{metric tons}}{50\,\text{hectares}} = 2\,\text{metric tons per hectare.}$$

For example, if 100 metric tons are produced on land measuring 50 hectares, then the crop yield would be 2 metric tons per hectare. These are standardized calculations that allow the comparison of crop performance across regions or seasons or even farming practices.

However, eventhough the formulae gives a simple and direct relationship of area to yield, it does not consider many other variables that will determine crop productivity. For this project, Yield was a key target variable and predictors included Area, Fertilizer, Rainfall, Pesticide Usage, Soil Nutrients and many others. These environmental and management variables that were incorporated in the machine learning models of this study go ahead to capture interactions that were not considered by the formula hence giving more precise yield predictions.

QUESTION 5: In some tasks, hyperparameter tuning had minimal impact. Why do you think this occurred?

In this project, hyperparameter tuning was mostly used to further refine the performance of the meta-models (SVR, XGBoost, and MLP), but it had a varying degree of impact for different tasks, mainly because:

1. The meta-models showed high baseline performance.

For tasks like crop classification, the default configurations of SVR and XGBoost already yielded very good results. For instance, SVR achieved 100% accuracy with default parameters, which means that the model captured relationships in the dataset so well that further optimization was not necessary. Since the baseline performance was already high, there was little room for improvement with hyperparameter tuning.

2. Ease of Certain Tasks

Crop classification is a relatively simple task, and its input-output relationships were strong and clearly distinguishable. Therefore, meta-models like SVR and XGBoost learned such patterns easily with their default settings. Hyperparameter tuning in this case did not make much difference, as the complexity of the task did not require further adjustments of model configurations.

3. Model Robustness

Both XGBoost and SVR are intrinsically robust models. XGBoost has regularization and smart optimization techniques, while SVR is good at handling nonlinear relationships due to its kernel functions. Their intrinsic design let them generalize effectively across tasks with little tuning.

4. Task-Specific Complexity

The simple tasks such as crop classification hardly benefited much from the tuning of hyperparameters, but the effect was immense in fertilizer prediction and to some extent, in yield prediction:

- In the tuned case, MLP obtained the minimum RMSE of 0.0294 and MAPE of 18.66% in predicting fertilizers, proving its ability in modeling complicated relationships.

- XGBoost with optimized hyperparameters by Grid Search greatly improved yield prediction with RMSE of 0.1583 and MAPE of 20.95%, suggesting the necessity of the tuning for a more variable regression task.

In conclusion, the influence of hyperparameter tuning on simpler tasks like crop classification was very limited due to the inherent robustness of the meta-models, the clear relationships in the data, and the high baseline performance of default configurations. However, for more complicated tasks such as fertilizer and yield prediction where variability is higher and complex dependencies exist in the data, hyperparameter tuning became significant. This approach ensured that resources were well utilized, focusing on tasks where tuning had the most impact while maintaining consistently high performance across all predictions.