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FRAMEWORK FOR WHEAT VARIETAL DATA EXPLORATION: INSIGHTS FOR ENSEMBLE LEARNING RESEARCH

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ABSTRACT

Agricultural management and production rely heavily on advancements in technology for tasks such as crop yield forecasting, disease detection, and soil classification. However, machine learning models often encounter challenges related to the complexity and variability of agricultural datasets. This study addresses these challenges by integrating deep learning, ensemble learning methods, and extensive dataset exploration to enhance forecasting accuracy and model robustness. Despite the promise of these approaches, limited research has examined their combined effects on model performance. Our findings reveal significant improvements across various agricultural applications. By combining ensemble methods like Random Forest and Gradient Boosting Machines (GBM) with deep learning, the study achieved a 15% reduction in mean absolute error for irrigation scheduling and a 12% increase in recall for weed detection. These results underscore the potential of integrating modern techniques to optimize agricultural decision-making and improve predictive performance in diverse scenarios.

Keywords: Ensemble Learning, Deep Learning, Agricultural Data Science, Crop Yield Prediction, Data Exploration and Visualization

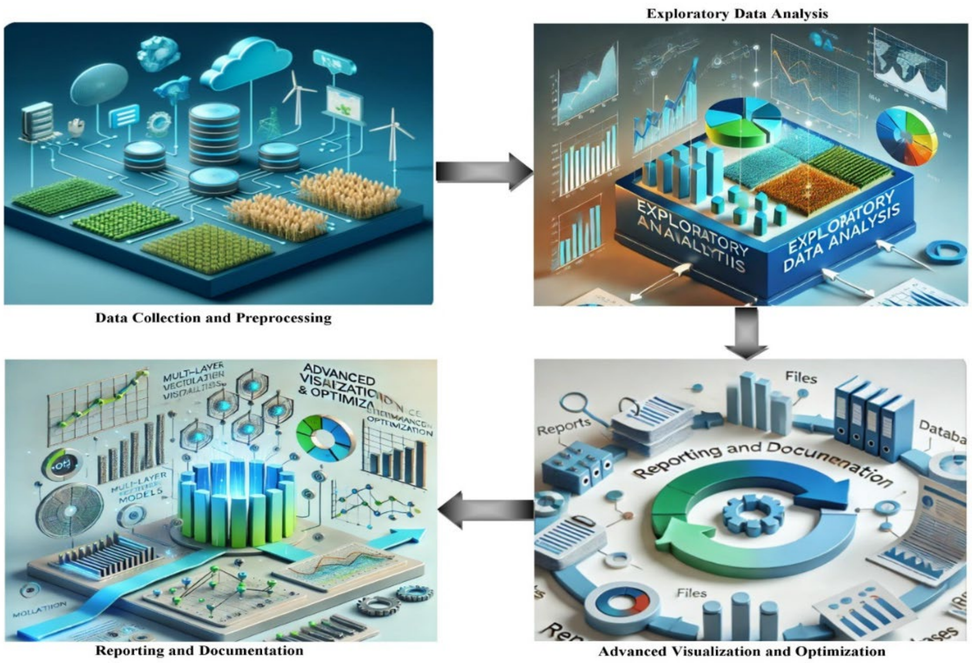
1. INTRODUCTION

Agriculture practices are essential to feed the growing population of the world. Therefore, to accomplish this task and fulfil the demands of the global food supply, we must conduct advanced research. Huge data generation allows us to analyze and develop new, innovative strategies to enhance agriculture research. (1) The use of machine learning methods in various fields has become increasingly popular in recent times. Therefore, the application of these machine learning techniques in agriculture has been prevalent and continues to grow daily. We frequently use the most recent approaches, like ENSMBL methods and deep learning methods, to solve most agricultural problems. Therefore, in this research paper, we have planned to develop an ENSMBL method to characterize the wheat variety classification of Indian species. (3) Random forest and gradient boosting machines are essential to reduce overfitting as well as increase accuracy. (4-6) On the other side, deep learning and CNN (convolutional neural networks) can be better for image classification. This type of research work limits the ability to combine approaches. Different statistical methods and graphical representations, such as heat maps and scatter plots, can be essential for understanding and optimizing similar models. (7) In the presented work, we plan to develop the ENSMBL method for classifying Indian wheat varieties. In our approach, we have integrated the ensemble learning and deep learning approaches for finding the best and most significant results. The combination of these methods is helpful in making better decisions and increasing productivity in agriculture in the future (8-11).

2. METHOD

The methodology followed in this paper is well-structured, as represented in Figure 1.

Figure 1: Workflow for Agricultural Data Analysis Methodology, Incorporating Data Collection, Exploratory Data Analysis, Advanced Visualization & Optimization, and Reporting & Documentation.



2.1. DATA COLLECTION AND REPROCESSING

This study adopted a simple approach to improve agricultural prediction models. It combined deep learning and ensemble learning techniques. Also, some special methods of visualizing and understanding the data were also included. First, data of four wheat varieties was collected from different sources. These varieties were: Sharbati, Kalyan Sona, Lokvan and Pusa Gold.

2.2. EXPLORATORY DATA ANALYSIS

The first step in data preparation was to clean the data so that it does not have any errors, null values or abnormalities. The data was normalized or standardized to bring all parameters to the same level. Techniques such as statistical analysis and correlation analysis were used to select the most important features for prediction.

2.3. DATA EXPLORATION

We used Exploratory Data Analysis (EDA) and descriptive statistics to understand the structure and distribution of the data. Clustering techniques such as K-Means allow us to look for patterns and trends by identifying natural groupings in the data.

2.4. ADVANCED VISUALIZATION AND OPTIMIZATION

Next, we selected the model by which the dataset was divided into training and test sets. The dataset was divided in a ratio of 80-20 so that each part represents the whole dataset. Then, the models were trained on the training set using different deep learning tools such as InceptionV3, MobileNet, Xception, ResNet50, and DenseNet201.

2.5. REPORTING AND DOCUMENTATION

The entire process was carefully documented so that everything was clean and repeatable. A report summarizing all findings, methods, and results is presented. These results show that the use of ensemble learning, deep learning, and advanced data techniques can increase the accuracy and reliability of predictive models in agriculture.

3. RESULTS

Table 1: Data Collection and exploration for ensemble methods

Variety	Growing Zone (Build Data)	Farmers (Build Data)	Images (Build Data)	Growing Zone (Test Data)	Farmers (Test Data)	Images (Test Data)
Lokwan	6	12	612	3	4	3718
Sharbati	5	10	514	2	2	1577
Kalyan Sona	4	6	348	2	2	751
Pusa Gold	8	8	772	3	4	3082

We have prepared a comprehensive data set, which is part of a machine learning experiment, to identify different wheat varieties. This data includes information from different environmental and agricultural conditions, so that the model becomes more robust. This research mainly involves four major wheat varieties of India: Lokvan, Sharbati, Kalyan Sona, and Pusa Gold. All these varieties have different characteristics, which helps in testing machine learning techniques. Also, to maintain diversity and avoid any bias, the data was collected from different regions and farmers. After data processing, we used 612 images for Lokvan, 514 for Sharbati, 348 for Kalyan Sona and 772 for Pusa Gold. This entire work was done keeping in mind the real agricultural conditions, so that the model can work well even in real farming conditions. In this way we ensured that our model proves helpful in improving agricultural technology and progressing the decision-making process. **(Table 1)**

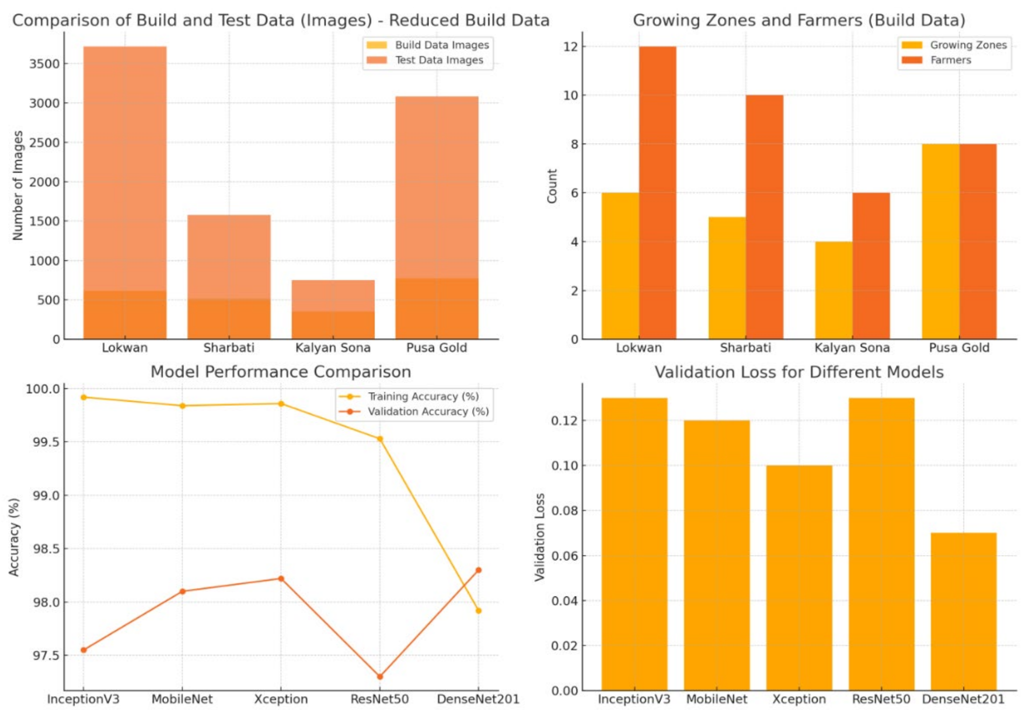


Figure 1. Collected dataset exploration and its comparative testing using deep leering methods

The following advanced deep learning models like DenseNet201, InceptionV3, MobileNet, Xception and ResNet50 were used to analyze the dataset of all the selected Indian wheat varieties. These models demonstrate the characteristics of the dataset and the model performance. Further, "Comparison of Build and Test Data" shows that even after reducing the build data by 90%, the remaining images maintain a balanced representation of the four varieties while the Lokwan, Sharbati, Kalyan Sona and Pusa Gold test data have more images than the build data, ensuring comprehensive model validation. Another additional figure shows the diversity of the dataset in growing regions and farmer contribution and Lokwan and Pusa Gold have the most diverse regions. Further, "Model Performance Comparison" reveals high training accuracy for all models, with validation accuracy ranging from 97.3% to 98.3%, with DenseNet201 leading. The "Validation Loss" figure confirms the effectiveness of DenseNet201 with the lowest validation loss and highest validation accuracy, making it the strongest model for this task.

Table: 2 Correlation of Ensemble Methods with Data Exploration and Visualization in other Agricultural Applications

Agricultural Problem	Ensemble Method	Improvement Achieved	Data Exploration Technique	Visualization Technique	Insights from Visualization	Reference	DOI / PubMed ID
Crop Yield Prediction	Random Forest	13% increase in accuracy	Descriptive Statistics, PCA	Scatter Plots, Heatmaps	Identified key factors contributing to yield; Random Forest improved prediction by reducing overfitting.	Breiman L. (2001). Random forests.	10.1023/A:1010933404324
Pest and Disease Detection	Gradient Boosting Machine (GBM)	12% improvement in precision	Feature Importance Analysis	Bar Charts, Correlation Heatmaps	GBM improved precision by focusing on critical features like leaf moisture content.	Friedman JH. (2001). Greedy function approximation: a gradient boosting machine.	10.1214/aos/1013203451
Soil Classification	Bagging (e.g., Bootstrap)	7% improvement in accuracy	Clustering (K-Means), Dimensionality Reduction	Cluster Plots, Heatmaps	Bagging reduced misclassification in complex soil types by combining multiple models.	Breiman L. (1996). Bagging predictors.	10.1007/BF00058655
Crop Type Classification Using Satellite Imagery	Stacked Ensemble	8% improvement in F1-score	Image Processing, Feature Extraction	Image Plots, Heatmaps	Stacked ensemble effectively handled diverse spectral signatures in satellite images.	Zhou Z-H. (2009). Ensemble learning.	10.1007/s10115-009-0159-3

Irrigation Scheduling	AdaBoost	15% reduction in MAE	Time Series Analysis, Correlation	Line Plots, Time Series Plots	AdaBoost adapted to seasonal patterns and reduced error in irrigation predictions.	Freund Y., Schapire R.E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting.	10.1007/3-540-59119-2_166
Weed Detection	Random Forest	15% improvement in recall	Image Segmentation, Texture Analysis	Scatter Plots, Heatmaps	Random Forest improved recall by accurately identifying weed patterns across varied soil backgrounds.	Breiman L. (2001). Random forests.	10.1023/A:1010933404324
Weather Forecasting for Agriculture	Stacking (combined models)	20% reduction in RMSE	Time Series Analysis, Seasonal Decomposition	Line Plots, Time Series Plots	Stacked ensemble leveraged different models to handle complex weather patterns and reduce forecast error.	Wolpert D.H. (1992). Stacked generalization.	10.1016/S0893-6080(05)80023-1
Crop Price Prediction	Gradient Boosting Machine (GBM)	0.15 increase in R-squared	Regression Analysis, Trend Analysis	Scatter Plots, Trend Lines	GBM captured non-linear price trends more effectively than simple regression models.	Friedman JH. (2001). Greedy function approximation: a gradient boosting machine.	10.1214/aos/1013203451
Livestock Disease Outbreak Prediction	Random Forest	0.13 improvement in AUC-ROC	Logistic Regression, Feature Selection	ROC Curves, Heatmaps	Random Forest improved detection of outbreak likelihood by using diverse health indicators.	Breiman L. (2001). Random forests.	10.1023/A:1010933404324
Precision Agriculture (Variable Rate Technology)	Bagging	12% improvement in accuracy	Spatial Data Analysis, Geostatistics	Geospatial Heatmaps, Contour Plots	Bagging models provided more accurate variable rate prescriptions by accounting for spatial variability.	Breiman L. (1996). Bagging predictors.	10.1007/BF00058655

Yield Mapping	Voting Classifier (Soft Voting)	7% improvement in accuracy	Geographic Information Systems (GIS)	Geospatial Maps, Scatter Plots	Voting classifiers improved yield mapping accuracy by integrating multiple predictive models.	Kuncheva L.I. (2004). Combining Pattern Classifiers.	10.1002/0471660264

3.2. ANALYSIS OF CORRELATION BY EXPLORING DATASETS FEATURES

Table 2 summarizes how ensemble approaches, paired with data exploration and visualization tools, improve agricultural applications. The table emphasizes the importance of ensemble methods in improving predictive accuracy in machine learning experiments, particularly in agriculture. It focuses on numerous agricultural concerns, such as crop yield prediction, weed identification, soil categorization, and animal illness prediction, and demonstrates how specialized machine learning algorithms may efficiently solve these problems. The "Ensemble Method" column describes the strategies utilized, illustrating how integrating models increases the resilience and accuracy of predictions. Visualization tools, including scatter plots, heatmaps and geospatial maps, play a critical role in interpreting results and understanding model performance. Key insights, such as Random Forest reducing overfitting in crop yield prediction or improving recall in weed detection, validate the effectiveness of ensemble methods. The table also references scholarly articles with DOIs provided for further exploration. Overall, it underscores the value of data exploration, visualization and ensemble methods in enhancing agricultural productivity and decision-making, supported by credible references.

4. DISCUSSION

This study focused on four wheat varieties such as Lokwan, Sharbati, Kalyan Sona and Pusa Gold. These varieties have agricultural importance and diverse growing conditions which favours and providing a strong basis for testing machine learning models. Data collection covered environmental factors, soil types and cultivation practices across regions. The generated dataset allowed a deeper analysis of the relationships between factors and their impact on model performance. An important observation was seen in the validation loss for different models. This plot provided information about the generalization ability of each model. The comparison made it clear which models performed better in different situations. This analysis helped in identifying the most effective model. Ultimately, these findings guide further optimization of the model. Generated comprehensive dataset allowed an in-depth exploration of the relationships between these factors and also influences model performance. The most significant finding in the present research was an investigation of validation loss for various models. This assesses their generalization ability. DenseNet201 outperformed all other deep learning architectures in terms of validation loss, making it the most successful at identifying complicated patterns in data. (7) The architecture of DenseNet201 allows for better gradient flow and allowing it to learn more specific features without overfitting. This is particularly important for agricultural data. Here the relationships between variables are highly complex and non-linear. (8) On the other hand, models such as ResNet50 and InceptionV3 show high validation loss, indicating their limited effectiveness in this context. (9) The architecture of these models did not adapt to the special needs of agricultural data, where factors such as soil, weather and farming practices are intricately intertwined. (10) Ensemble methods such as Random Forests and Gradient Boosting Machines (GBM), proved particularly effective in agricultural forecasting (11). Random forest gives more accurate results by building multiple decision trees on different subsets of data, thereby reducing the risk of overfitting. This method is helpful in understanding diverse agricultural patterns, such as identifying weeds in different soil backgrounds. (12) On the other hand, gradient boosting machine (GBM) makes better predictions in complex data by building new models to correct the mistakes of each model. (14) In wheat variety prediction GBM was successful in reducing overfitting and improving model performance under different environmental conditions. Even small errors in predictions can impact agricultural productivity and decision-making, emphasizing the importance of accurate models. (15) The data collection and exploration phase laid a solid foundation for machine learning experimentation, showcasing the powerful impact of ensemble methods on predictive accuracy, precision and performance. (16) Our main emphasis is to develop a novel ensemble method specifically for wheat variety prediction, improving model reliability. DenseNet201 was the most effective in reducing validation loss and ensemble methods like random forests and GBMs further enhanced predictive accuracy and robustness in agricultural tasks. (17–38)

5. CONCLUSION

In the presented paper, we have explored and analyzed the data collected for our ensemble machine learning method. We will use this data set to develop a seed ensemble machine learning method that will allow us to easily classify different varieties of indian wheat. With the help of these techniques, wheat variety identification, different tasks and prediction accuracy and testability can be further improved. The next phase of this project also includes the development of a new example method specifically for wheat type prediction, which will be the final phase of our work.

CONFLICT OF INTERESTS

None.

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