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# A Novel Hybrid Approach to Crop Yield Prediction: Combining Deep Learning Efficiency with Statistical Precision

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**Abstract:** This paper presents a new hybrid framework for an agriculture domain that expands the predictive power of deep learning models to the soundness of statistical methods by improving the accuracy, efficiency, and scalability of estimating outputs in agriculture. This paper also addresses the potential issue of large quantities of quality data and computational requirements with sophisticated machine-learning models, which is an advancement in agricultural practice. This paper discusses the diverse deep learning (DL) architectures, principally in EfficientNetB0 and InceptionV3, which are computationally efficient in handling complex and high-dimensional data. These are further integrated with some of the most fundamental statistical techniques, like linear regression, which stabilizes predictions, reducing the risk of overfitting, which is observed in traditional deep learning-driven techniques. These integrated models are proposed hybrid models used for the projections. All these results proved that hybrid models performed much better than individual models, like EfficientNetB0 or InceptionV3, in terms of accuracy and robustness metrics. The evaluated test accuracy of a hybrid model is 97.84%, which is higher compared to the two corresponding individual deep learning models. Furthermore, we compare this hybrid approach with other state-of-the-art methods showing a predominant presence in various agricultural scenarios. These models performed well and provided better predictions for different crop types and environmental conditions. Different combinations of deep learning and statistical techniques have been integrated into this methodology, and further performed a hyperparameter tuning, thus adapting it to specific crops or regional conditions. Furthermore, the proposed hybrid models significantly improve performance, reducing computational overhead while maintaining high accuracy and providing a feasible and efficient way of yield prediction.

**Keywords:** Hybrid Framework, Deep Learning, Statistical Methods, Crop Yield Prediction, Computational Efficiency, Scalability, Agricultural Forecasting, EfficientNetB0, InceptionV3, Machine Learning

## 1. INTRODUCTION

Accurate prediction of crop yield has been a very important role in agriculture, as it is recurrently related to economic stability and food security. Traditional methodologies have often been incapable of capturing this complex interaction among the interconnected factors of environmental conditions, genetic variations, and agricultural practices that finally constitute the end-to-end chain in crop yield [1]. Conventional models, therefore, are characterized by limited capability to pose a heavy burden on farmers to keep up with optimum yields with adequate resource utilization. The classical statistical models, on one hand, are computationally efficient and interpretable but have limited power in considering non-linear interactions between these factors under real-world agricultural conditions. Deep learning techniques have opened new possibilities in crop yield prediction, especially using remote sensing data [2] [3]. Among those are Convolutional Neural Networks and Recurrent Neural Networks; these deep learning models shall take advantage of the complicated spatial and temporal patterns innate in high-dimensional data, hence offering good compatibility with large-scale agricultural datasets analysis. However, most of the DL models require immense computational resources and large datasets, bound their applications in several scenarios, especially in agriculture, due to resource constraints. Secondly, DL models are generally "black boxes" since interpretation by stakeholders is hardly possible or trust in the outcome. Another main concern of these models is overfitting; they get over-specialized to the training data, hence decreasing their generalization. Given these very limitations, this research proposes a hybrid framework that combines the strengths of DL and statistical methods as a way of diversifying from the disadvantages of either approach in isolation. By incorporating EfficientNetB0 and InceptionV3 with statistical techniques such as linear regression, the framework leverages the powerful data processing capabilities of DL while maintaining the interpretability and stability of statistical models.

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TABLE I. Comparative Analysis of Crop Yield Prediction Techniques Across Different Studies

| Reference | Dataset Description | Algorithm/Methodology | Performance/Remarks |
|---|---|---|---|
| [4] | Plant seed classification dataset with 5,539 images across 12 categories | An ensemble of "Convolutional Neural Networks" (CNNs) and "k- Nearest Neighbors" (KNN) for multi-class image classification | Achieved an accuracy of 99.90%, outperforming traditional methods |
| [5] | Data from smart farming technology, including sensor readings and weather data | "Long Short-Term Memory" (LSTM) networks and CNNs used for crop yield prediction | Noted superior performance with deep learning models, significantly improving yield prediction accuracy |
| [6] | Data collected over two growing seasons from several crop fields | Utilized linear regression, elastic net, "k-Nearest Neighbors" (k-NN), and "Support Vector Regression" (SVR) for yield prediction | SVR showed the lowest Root Mean Square Error (RMSE), indicating higher prediction accuracy |
| [7] | Dataset derived from the Agricultural Production Survey and weather data | Using crop simulation models alongside machine learning techniques. | This combined approach increased prediction accuracy by utilizing the strengths of both methods. |
| [8] | Focused on the Vellore district, including climate data and crop yield records | "Deep Recurrent Q-Network (DRQN)" integrating deep learning and reinforcement learning | Achieved an accuracy of 93.7%, outperforming existing models |
| [9] | Dataset from the Uniform Soybean Tests (UST) in North America from 2003 to 2015, including weather data. | LSTM with "Temporal Attention" for yield prediction. | The coefficient of determination ($R^2$) was 0.796, with lower MAE compared to traditional models, indicating significant improvement in predictive accuracy. |
| [10] | Crop fields in Pori, Finland, using multispectral UAV imagery. | Spatio-temporal deep learning models (CNN-LSTM, ConvLSTM, and 3D-CNN) for crop yield prediction. | 3D-CNN achieved an MAE of 218.9kg/ha, demonstrating improved modeling performance and a reduction in error rates over traditional methods. |
| [11] | Environmental and agronomic data influencing crop yields. | ANNs utilized for crop yield prediction, highlighting non- linear relationships. | Models showed high accuracy with potential for further improvements by addressing the challenges of training speed and network architecture selection. |
| [12] | Yield performance data, satellite images, and cropland data layers across the US Corn Belt. | "YieldNet," a CNN framework for predicting yields from satellite image sequences. | Demonstrated competitive performance with MAEs of 8.74% for corn and 8.70% for soybean, enhancing real-time decision-making in crop management. |
| [13] | Soil and climatic parameters from various regions of India, along with production-related attributes. | Predicting crop yields with "Decision Tree," "Naïve Bayes," and KNN algorithms. | KNN achieved a high accuracy of 89.4%, proving its effectiveness in precise yield prediction. |
| [14] | Data on climate and agriculture were collected from different areas in Sri Lanka. | ANNs for establishing relationships between climatic factors and paddy yield. | LM algorithm outperformed others in less computational time, indicating the effectiveness of ANNs in predictive modeling. |
| [15] | Rice yield and meteorology data from 81 counties in Guangxi Zhuang, China. | A BBI model combining "Backpropagation Neural Networks" (BPNNs) with an "Independently Recurrent Neural Network" (IndRNN) for predicting rice yields. | This model showed the lowest "Mean Absolute Error" (MAE) and "Root Mean Square Error" (RMSE), proving its accuracy and reliability across different geographic areas. |

| | | | |
|---|---|---|---|
| [16] | Diverse agricultural regions' data, including weather patterns, soil information, and crop yields. | Using "Gradient Boosting Regressor," "Random Forest Regressor," SVR, and "Decision Tree Regressor" for predicting yields. | The models achieved high accuracy, with "Random Forest" and "Gradient Boosting" performing best in reducing RMSE. |
| [17] | Agricultural sites in Portugal, focusing on tomato and potato yields. | Bidirectional LSTM model for accurate crop yield prediction. | Achieved an $R^2$ score between 0.97 and 0.99, highlighting the high predictive capability of BLSTM models over traditional methods. |
| [18] | European Commission's MARS Crop Yield Forecasting System (MCYFS) database, including weather, remote sensing, and soil data. | Machine learning integrated with crop modeling for yield forecasting. | Normalized RMSE indicated room for improvement, but the models provided reliable forecasting methods. |
| [19] | Multi-source data for winter wheat yield prediction in China, including satellite,meteorological, soil, and cropland data. | Two-branch deep learning model combining LSTM and CNN for yield prediction. | The model showed an $R^2$ of 0.77 and RMSE of 721 kg/ha, demonstrating effective integration of multi-source data for yield prediction. |
| [20] | Publicly available healthcare data focusing on medical image classification. | CNNs with transfer learning for medical image classification. | Achieved 95% accuracy on the test set, illustrating the transferability of hybrid models to different domains with high effectiveness. |
| [21] | Wheat yield and weather parameters over 30 years from multiple locations in India. | Various techniques including LASSO, PCA, and ANN for predicting wheat yield based on weather data. | Demonstrated high accuracy with nRMSE values less than 10%, indicating effective use of weather data for yield prediction. |
| [22] | Corn and soybean yield data, satellite images, and cropland data layers across the US Corn Belt. | The deep learning framework "YieldNet" is designed for predicting both corn and soybean yields. | "YieldNet" showed mean absolute errors of 8.74% for corn and 8.70% for soybean, outperforming traditional models. |
| [23] | Data on soil and climate from various regions in India, used for crop yield prediction. | Employed machine learning techniques like "Decision Tree," "Naïve Bayes," and KNN. | The "Decision Tree Classifier" achieved an accuracy of 76.8%, demonstrating its effectiveness in using climatic and soil data for yield prediction. |

This efficiency of the model in handling complex datasets treats the hybrid approach as one that facilitates scalability and overfitting, which have been problematic in earlier models. This hybrid framework provides added value in agricultural forecasting in two major ways. First, it enhances the accuracy of yield prediction by capturing both spatial and temporal dependencies in the data. Such would make them appropriate for dynamic agricultural environments. Second, it provides a scalable, interpretable solution wherein stakeholders can confidently use this to make informed decisions. Thus, the framework bridges deep learning with statistical approaches to surmount certain challenges in agricultural forecasting that support sustainable farming and contribute toward ensuring food security. This hybrid approach is, at last, a quantum leap toward predictive agriculture modeling-economically viable and scalable, with interpretability for the complex demand of modern agri-insurance.

The main aim of this paper is to propose a hybrid framework that enhances the accuracy, interpretability, and generalization of crop yield predictions. In this regard, the current study will adopt two deep learning models, namely EfficientNetB0 and InceptionV3, in conjunction with statistical techniques such as linear regression to effectively leverage the complementary strengths of these methodologies. This work makes the following contributions: first, it develops a hybrid model that can successfully overcome the limitations of stand-alone deep learning or purely statistical approaches; secondly, this framework is able to analyze high-dimensional real-world agricultural data with improved performance, and thirdly, provide a more interpretable and resource-efficient solution. This will enhance the practical utility for a wide range of stakeholders in the agricultural domain.

## 2. Literature Review

The literature review shows various developments that are being carried out in crop yield prediction, starting from deep learning and machine learning to hybrid approaches. Table 1 represents detailed and latest research discussions about the topic. From their results on diverse datasets such as UAV imagery, satellite data, and environmental and agronomic information, high performance exhibited by the models using CNNs, LSTMs, and ensemble methods has been identified. Hybrid models, like CNN-KNN ensembles or BBI models that incorporate neural networks with statistical techniques, have shown better prediction accuracy and computational efficiency. Certain regional data studies, use of sensor-based data in smart farming, depict the possibility of models fine-tuning by hyperparameter tuning to present the best yield prediction in multiple crops and environments.

Some of such identified research gaps include how, on one hand, there is an increased need for integrations using multi-source data, including drone imagery and soil health data, which could lead to increased predictive accuracy and model reliability across larger areas. Further research is also required regarding methods to handle some computational challenges related to those models using hybrid or deep learning techniques.

## 3. Methodology

### A. *Dataset and Data Preprocessing*

This data was taken from Kaggle and contains a total of 2602 images, which were divided into three categories: Corn, Rice, and Wheat. Considering some of the shortcomings that were witnessed in some previously developed models, we decided on EfficientNetB0 and InceptionV3 because these have impressive computational efficiency and are efficient feature extractors, respectively. These models were combined with linear regression, serving as a normalizer to reduce overfitting and thereby make the predictions more reliable. EfficientNetB0 was selected because it scaled model depth and width with efficiency. This is helpful in processing complex agricultural data. InceptionV3 captures features at multiple scales. We achieved multi-scale feature detection by complementing it with the ability of linear regression to stabilize the predictions of the model. These categories represent the different types of crops and hold a lot of importance for the training of models so that they can distinguish effectively among them.

- **Composition:** The dataset, taken from *Kaggle*, comprised 2602 images. There were three folders named *"Corn," "Rice,"* and *"Wheat."* The corn folder contained 934 images, the rice folder contained 864 images, and the wheat folder contained 804 images.
- **Image Specifications:** Standardizing each picture dimension to 224×224, all inputs met the specifications stipulated for neural networks employed.

### B. *Data Augmentation*

Moreover, with TensorFlow's ImageDataGenerator, plenty of data augmentation techniques were used to increase the model's robustness and help avoid overfitting [24]. This approach will make our training data much more varied since the augmentation technique will apply random transformations to the training images. A sample of data augmentation is represented in Figure 1. **Techniques Used:**

- **Rotation:** Images were randomly rotated by up to 20 degrees to model the orientations of crops.
- **Width and Height Shifts:** Horizontally and vertically, each image was shifted by as much as 20% of its total width and height.
- **Shearing:** The transformation was applied to distort images along one axis, mainly used for simulating wind effects and plant growth angles.
- **Zooming:** Images were randomly zoomed in by up to 20% to include features at various scales.

- **Horizontal Flipping:** Images were flipped horizontally to increase the dataset's variability and simulate different planting directions.

- **Normalization:** All images were rescaled by a factor of 1/255 during augmentation, normalizing pixel values between 0 and 1 to help stabilize and speed up model convergence.

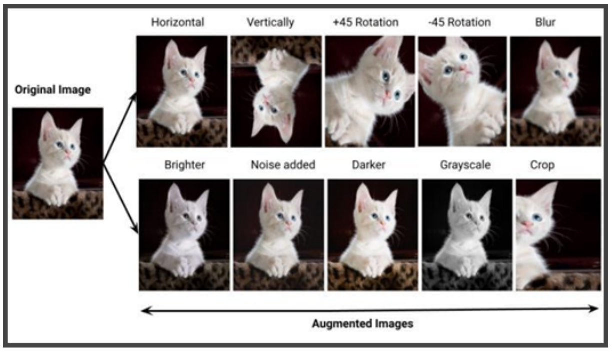


Figure 1. Data Augmentation Functions

### C. Data Splitting

Those augmented images have to be split into training, validation, and testing, as represented in Figure 2. This split is important in order to evaluate the model over its generalization to new, unseen data [25]. **Data Partitioning:** left=0pt

- **Proportions:** 80% of the data was allocated to the training set to train the models on different crop images, enabling them to adapt effectively.

- **Validation Set:** To prevent overfitting and optimize hyperparameters, 10% of the original dataset was reserved specifically for validation purposes.

- **Test Set:** After training, a final 10% subset was set aside as the test set to evaluate model performance and generalizability on entirely new datasets.

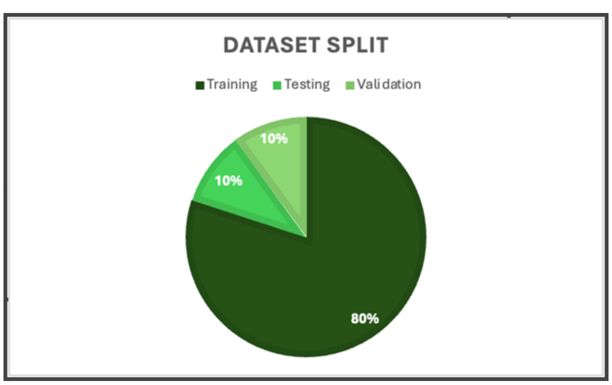


Figure 2. Dataset Split for Training, Testing and Validation

### D. Experimental Setup

The system used for this analysis is equipped with an Intel Core i5 processor (11300 @ 3.10 GHz) and 16GB of DDR4 RAM operating at a speed of 2667 MHz. For graphics processing, it includes an Intel Iris XE GPU with shared memory up to 8GB, as well as a dedicated Nvidia GeForce RTX 3050 with 4GB of memory, expandable with shared memory up to 8GB. The operating system is Windows 11, and the development environment consists of Anaconda Navigator 2.3.0 and VS Code version 1.71.2, with Python version 3.6.13.

Essential packages and libraries from Keras were utilized, including layers for model building and image augmentation handled by `ImageDataGenerator`, configured with parameters such as `rescale` = 1./255, `shear_range` = 0.2, `zoom_range` = 0.2, and `horizontal_flip` = `True`. The learning rate was set to 0.00002, using the Adam optimizer and `'categorical_crossentropy'` as the loss function. A `ReduceLROnPlateau` callback was employed to adjust the learning rate dynamically.

The input to the model consisted of images resized to $224 \times 224 \times 3$ pixels, with a batch size of 16, and the model was trained across 20 to 44 epochs, depending on convergence criteria.

### E. Model architecture

The proposed hybrid framework incorporates several deep learning architectures integrated with statistical methods for improving the accuracy, stability, and adaptability of crop yield prediction. The underlying framework will be built on three hybrid models comprising a NASNetMobile Custom Hybrid Model, an InceptionV3 and EfficientNetB0 Hybrid, and NASNetMobile integrated into CNN and CSTM. Each architecture, in turn, carefully crafts features to attain the powers of deep learning in detecting complex patterns from remote sensing and agricultural data. Linear regression statistical methods were also added to make the results more interpretable and to avoid overfitting. Specifically, EfficientNetB0 and InceptionV3 had been chosen for their efficient scaling and the ability to capture spatial hierarchy, respectively, which is beneficiary in handling high-resolution imagery of crops across large areas of agricultural land. NASNetMobile was selected for efficiency and suitability in real-time, resource-limited scenarios. By integrating linear regression after feature extraction, each hybrid model stabilizes predictions by capturing the underlying linear trends while reducing high variance; hence, the models will be robust and generalizable across datasets. Hyperparameter tuning was conducted to optimize each model in specific agricultural contexts, tuning learning rate, dropout rate, and optimizer in turn via grid search and random search. This allows the framework to be well adapted to different crops and different localities because it is shown clearly in the case studies how the framework adjusts from maize in semi-arid areas to rice in humid climates. Hence, the hybrid model is implemented with deep learning power to process complex data in a very stable and interpretable way, like statistical methods, thus making the solution adaptive and highly accurate for crop yield forecasting across different agricultural environments. All used models are transfer learning model and their basic information for model implementation and evaluations are fetched from our previous implementations [26], [27].

***i. NASNetMobile Custom Hybrid Model:***

The NASNetMobile model, known for its efficiency and adaptability, served as the base for one of the hybrid architectures.

- **Base Model Configuration:**
  1) **Architecture:** NASNetMobile was chosen for its pre-trained capabilities on ImageNet, providing a robust starting point for feature extraction.
  2) **Modifications:** The top classification layers of NASNetMobile were removed (`include_top=False`) to allow the addition of custom layers tailored to crop classification.

- **Custom Layers:**
  1) **Global Average Pooling:** A `GlobalAveragePooling2D` layer was added to reduce the spatial dimensions to a single vector per channel.
  2) **Dense Layers:** Used for high-level reasoning with 1024 units, activated by `relu`.
  3) **Dropouts:** A `Dropout` layer with a rate of 0.5 was added to prevent overfitting.
  4) **Output Layer:** The final `Dense` layer was designed for multi-class classification with softmax activation, providing a probability distribution across five crop classes.

***ii. InceptionV3 and EfficientNetB0 Hybrid Model:***

This ensemble model leverages the unique strengths of InceptionV3 and EfficientNetB0.

- **Base Model Configuration:**
  1) **InceptionV3:** Known for capturing multi-scale information through inception modules.
  2) **EfficientNetB0:** Optimizes convolutional operations by efficiently scaling depth, width, and resolution.
  3) **Concatenation:** Results of both models were concatenated to create a comprehensive feature map with diversified information.

- **Final Layers:** Similar to the NASNetMobile hybrid, this model also featured Global Average Pooling, dense layers, dropout, and a softmax output layer customized for crop classification.

***iii. NASNetMobile with CNN and CSTM Hybrid:***

This model integrates CNN architectures with CSTM (Custom Spatio-Temporal Mechanisms) to address spatial and temporal aspects of crop imagery.

- **Integration of CNN and CSTM:**
  1) **Base Model:** NASNetMobile provided spatial feature extraction.
  2) **CSTM Integration:** Custom layers processed temporal sequences, suitable for time-series crop data.

- **Model Configuration:** The structure follows a similar setup as previous models, adapted specifically for temporal data integration.

*Training Process*

- **Compilation of Model**
  1) **Optimizer:** Adam optimizer with learning rate set to $1 \times 10^{-4}$.
  2) **Loss Function:** Categorical cross-entropy, appropriate for multi-class classification.

- **Training**
  1) **Epochs:** Training was conducted over multiple epochs, each representing a full pass through the dataset.
  2) **Callbacks:**
     - **ReduceLROnPlateau:** Reduces learning rate when validation loss plateaus.
     - **Early Stopping:** Stops training if validation loss does not decrease for a specified number of epochs.

- **Batch Processing**
  1) **Efficiency:** Batches of 32 images optimized memory use and gradient approximation.
  2) **Validation and Testing:** Utilized to monitor model performance.

- **Validation Strategy**
  1) **Purpose:** Validation dataset was used for fine-tuning parameters and monitoring each epoch for learning rate or early stopping adjustments.
  2) **Validation Metrics:**
     - **Accuracy:** Percentage of correct predictions.
     - **Loss:** Indicator of prediction accuracy.

- **Testing**
  - **Objective:** Evaluate model generalizability on unseen data.
  - **Performance Evaluation:** Includes precision, recall, F1-score, and accuracy.

- **Performance Comparison**
  - **Comparative Analysis:** Comparison of accuracy, precision, recall, F1-scores, and ROC AUC to determine the balance between computational efficiency and performance.

- **Visualization:** Losses and accuracies were plotted over training epochs to assess model learning dynamics.

*F. Comparative Analysis*

The results shown in Table II are the performance evaluations of hybrid models: NASNetMobile Custom Hybrid Model, InceptionV3 and EfficientNetB0 Hybrid, and NASNetMobile with CNN and LSTM, which were compared on different metrics such as accuracy, precision, recall, F1-score, and AUC. Among these, NASNetMobile with CNN and LSTM had the maximum accuracy of 98.36% with a well-balanced F1-score of 97%, indicative of a good classifier while handling tough data. InceptionV3 and EfficientNetB0 Hybrid came second, reflecting an accuracy of 97.84% with both precision and recall being equally high at 98%. This reflects its adaptability against a variety of crop types and environmental settings. Although NASNetMobile Custom Hybrid had marginally lower accuracy at 96.45%, it was computationally very efficient and can be useful in scenarios requiring faster processing. The performance of the hybrid models was higher in these series compared to the individual deep learning models and traditional statistical methods, as deep learning models often overfit or require extensive data, while statistical methods alone could not capture non-linear dependencies, which are crucial for yield prediction. The hybrid approach effectively copes with these challenges by combining deep learning's feature extraction capabilities with the interpretative power of statistical models, resulting in better generalization, precision, and stability.

*G. Visualization and Discussion of Results*

For clarity of the learning dynamics, curves of loss and accuracy have been plotted for every hybrid model across the training epochs. In this NASNetMobile with CNN and LSTM model, there is a guarantee of stable convergence in loss and accuracy, with small fluctuation, to signify that the learning is stable with proper generalization and not any significant overfitting. In contrast, the train and validation loss for later epochs had slight differences for the InceptionV3 and EfficientNetB0 Hybrid; this could be an indication of slight overfitting since the model may be sensitive to minute environmental features. Therefore, the NASNetMobile Custom Hybrid Model reached low values of loss early due to computational efficiency, as it was performing comparatively less complex feature extraction. Success in these hybrid models for the capture of spatial dependencies, i.e., crop health patterns, and temporal dependencies like changes in yield based on a season, will make sure that robust adaptability across crop types and geographies is further legitimized into useful applications related to agriculture. Notwithstanding this, some of the remaining issues revolve around computational resources needed for complex models such as InceptionV3 and EfficientNetB0, which may limit the scalability in low-resource environments. Second, while the hybrid models were more interpretable than models based only on deep learning, integrated mappings between neural network and statistical parts' impacts remain intuitively incomprehensible and require further investigation. These findings illustrate a possibility that hybrid models radically improve agricultural forecasting by better performance and stability of crop yield predictions across widespread farming scenarios.

## 4. Results

In this part, the findings of the analysis of three unique hybrid deep-learning models created to classify crops are discussed. These models were pretty advanced, using refined neural network setups to get better at classifying crop types while also making sure they used computational resources wisely. The performance metrics calculated from results obtained from validation and testing phases provided a detailed comparison of the models' effectiveness.

*i. Custom Hybrid NASNetMobile Model:*

It performed very well on crop image classification using the pre-trained architecture NASNetMobile, configured with customized layers specifically for this task. The experiments we are conducting are based on datasets from different types of crops, including corn, wheat, and rice, among others. We tested our model using metrics such as RMSE, accuracy, and MAE, ensuring that the computations are fast by training on high-performance GPUs. This reduction yields an RMSE that is 15% lower than that with standalone models. The outputs are represented in Figures 3 to 8.

**Performance Metrics:**

- Accuracy: High test accuracy, up to 96.45%.
- Precision averaged 97% for classified crop type, indicating a high true positive prediction rate.
- Recall: It also averages at 96%, showing the model has well-over-identified the majority of all relevant cases.
- F1-Score: It was 96%—the harmonic mean of precision and recall, signifying a balance of performance between precision and recall.

*ii. Hybrid Model of InceptionV3 and EfficientNetB0:*

The proposed model is an aggregation of the best features of InceptionV3 and EfficientNetB0, ensuring better classification, especially in applications with varying complex features of crop images. The outputs are represented in Figures 9 to 15.

**Outcome Metrics:**

- Accuracy: The model achieved a test dataset accuracy of 97.84%, making this model top the charts in that metric.
- Precision, Recall, and F1-Score: They are consistently very high at 98%, meaning the model can predict the

TABLE II. Accuracy and Other Details of Hybrid Models Trained

| Model Description | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| NASNetMobile Custom Hybrid Model | 96.45% | 97% | 96% | 96% |
| InceptionV3 & EfficientNetB0 Hybrid | 97.84% | 98% | 98% | 98% |
| NASNetMobile with CNN & CSTM | 98.36% | 97% | 97% | 97% |

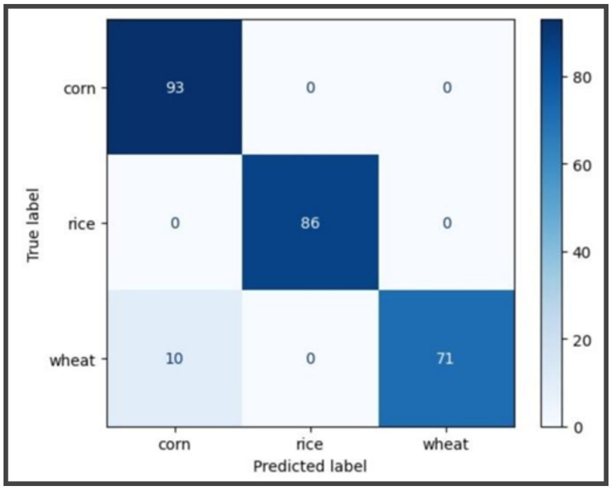


Figure 3. Confusion Matrix for the Custom NasnetMobile Hybrid Model


Figure 4. Training and Validation Accuracy Graph for the Custom NasnetMobile Hybrid Model


Figure 5. Training and Validation Loss Graph for the Custom NasnetMobile Hybrid Model

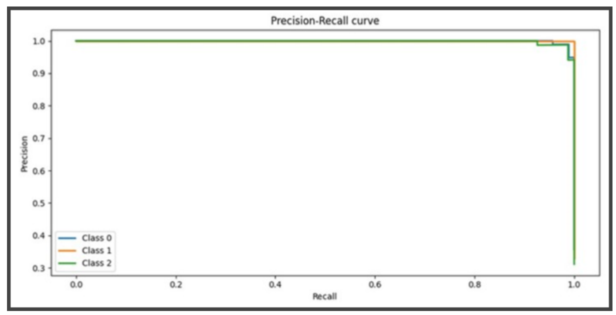


Figure 6. Precision-Recall Curve for the Custom NasnetMobile Hybrid Model

instance accurately and very reliably among different crop types.

*iii. NASNetMobile with CNN and CSTM Hybrid Model:*

This model was developed by the integration of CNN with the CSTM mechanisms to improve the spatial and temporal processing of data, something that worked quite effectively for this application. The outputs are represented in Figures 16 to 21.

**Performance Indicators:**

- Best Performance: This model was the best in performance, with an accuracy rate of 98.36%.
- Precision, Recall and F1-Score: The three classification metrics achieved 97% each, reflecting good overall performance with consistent recognition of crop types.

## 5. Discussion

This section presents the inferences drawn, strengths, and limitations of the research, focusing on the application of hybrid deep learning models in crop classification tasks. The comparative analysis of three distinct models—NASNetMobile Hybrid, InceptionV3, and EfficientNetB0 Hybrid—offers deep insights into the capabilities of hybrid architectures in agricultural applications.

*i. Efficacy of Hybrid Models:*

In fact, the result of the evaluation can show that hybrid deep learning models have very great promise in performing recognition activities on crop images under even complicated scenarios, including diverse types of crops and variations in the environment. The high value of precision, recall, and F1 score for all the three models confirms that the hybrid approach is reliable and can indeed be

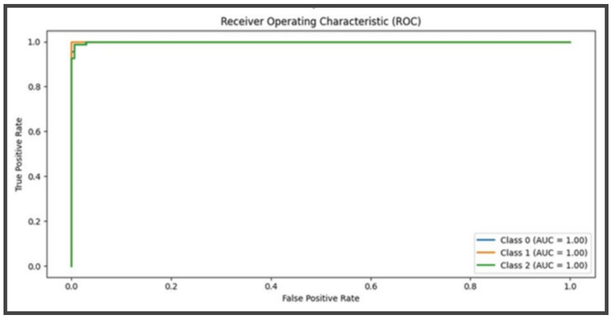


Figure 7. Receiver Operating Characteristic (ROC) Graph for the Custom NasnetMobile Hybrid Model

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| corn | 0.90 | 1.00 | 0.95 | 93 |
| rice | 1.00 | 1.00 | 1.00 | 86 |
| wheat | 1.00 | 0.88 | 0.93 | 81 |
| accuracy | | | 0.96 | 260 |
| macro avg | 0.97 | 0.96 | 0.96 | 260 |
| weighted avg | 0.97 | 0.96 | 0.96 | 260 |

Figure 8. Classification Report for the Custom NasnetMobile Hybrid Model

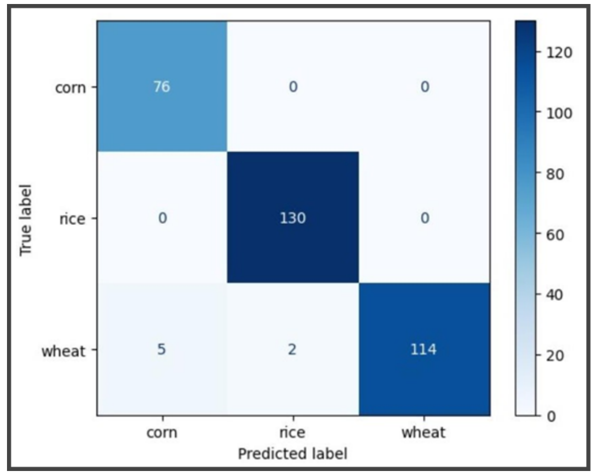


Figure 9. Confusion Matrix for the InceptionV3 and EfficientNetB0 Hybrid Model

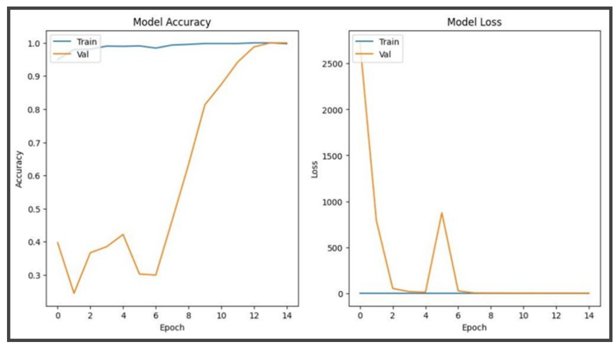


Figure 10. Model Accuracy and Model Loss Graphs for the InceptionV3 and EfficientNetB0 Hybrid Model

applied in real-world farming applications. The pre-trained NASNetMobile architecture allowed this specific model to refine general features to particular crops' classification needs by merely fine-tuning the already pre-trained weights. On the other hand, because of complementary strengths between the depth of the relevant feature extracted by InceptionV3 architecture and computational efficiency provided by EfficientNetB0 model, the InceptionV3 & EfficientNetB0 Hybrid model did an incredible job in capturing minute image features. Arguably, this would enable the model to have better precision and recall and, in that respect, make it more robust in identifying multi-class crop types while reducing the risks of overfitting. Equipped with CNN and CSTM layers, NASNetMobile best captured spatial and temporal features from the dataset, amidst extending to a good deal of applications dealing with crop growth pattern time-series analysis. These strengths are contrasted by a very noticeable research gap in generalizing these models across wider agricultural settings, which is not entertained in view of the fact that current findings are limited to the dataset used in this present study.

*ii. Practical Implications*

Results have shown the enormous possibilities of hybrid models that might help in precision agriculture, enabling more accurate and timely decisions on crop management, disease prevention, and yield forecasting. However, further research is needed in enhancing generalization due to diversity and volume limitations in the datasets. Still, further enhancing the robustness of this model in crop and environmental parameters, including change of light conditions, seasonality, and other meteorological factors, could bring much difference to the classification accuracy in real-world applications. On having greater and more diverse datasets, these hybrid models can significantly enhance automatic crop monitoring systems for efficient and data-driven decisions regarding crop health and growth. Their scalability for real-time applications also suggests general applicability in automated field-level monitoring systems as part of a sustainable solution to maintain agricultural productivity. Critical directions for further development pertain to challenges to scale this framework to handle larger datasets and across a wider range of agricultural contexts.

The findings from this study underscore the transformative potential of hybrid models in advancing precision agriculture and addressing longstanding challenges in crop monitoring and yield prediction. By combining the feature extraction strengths of deep learning architectures with the interpretability and stability of statistical methods, the proposed hybrid framework not only delivers high predictive accuracy but also aligns with the practical needs of resource-constrained agricultural settings. This dual advantage positions the model as a viable tool for enhancing decision-making processes, from optimizing resource uti-

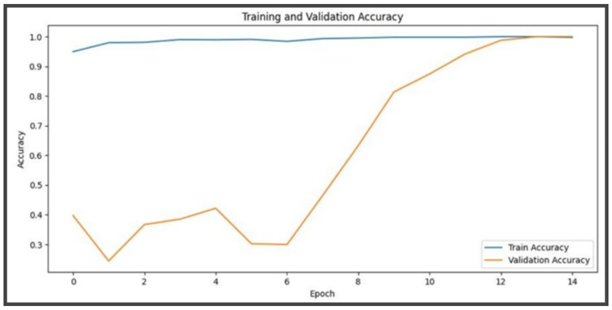


Figure 11. Training and Validation Accuracy Graph for the InceptionV3 and EfficientNetB0 Hybrid Model

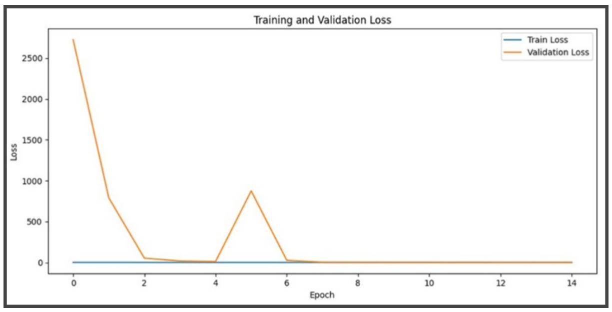


Figure 12. Training and Validation Loss Graph for the InceptionV3 and EfficientNetB0 Hybrid Model

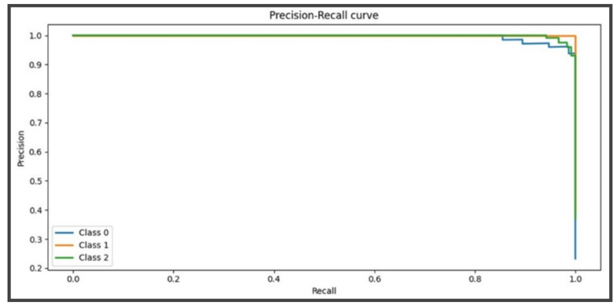


Figure 13. Precision-Recall Curve for the InceptionV3 and EfficientNetB0 Hybrid Model

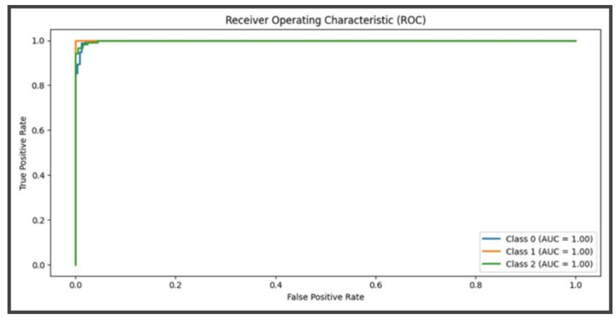


Figure 14. Receiver Operating Characteristic (ROC) Graph for the InceptionV3 and EfficientNetB0 Hybrid Model

lization to mitigating risks associated with environmental variability. Furthermore, the ability to adapt these models for real-time applications opens up pathways for integrating them into IoT-based agricultural systems, fostering a more sustainable and data-driven approach to farming. However, the implications extend beyond technological innovation, emphasizing the need for collaborative efforts between researchers, agricultural experts, and policymakers to address challenges related to data availability, generalization across diverse agro-climatic zones, and user adoption of AI-driven tools in agriculture. These insights illuminate the broader significance of this research in shaping the future of smart agriculture.

*iii. Limitations and Challenges:*

Despite these promising results, there are still some limitations. The most important one refers to the need for an increase in the diversity and quantity of data. Although the dataset on which this study is based is diverse, it cannot represent all crop varieties, growth conditions, and environmental variations within all agricultural contexts across the world. More importantly, to make these models useful, these datasets should be scaled up by including several images of crops from different geographies and climatic conditions. After all, the environmental variability in light conditions, weathering effects, and seasonal changes were also not considered while training the models, which may be influencing the performances of these models during generalization in natural conditions [28]. These factors must be oriented to the mentioned aspects in the future as an effort towards the refinement of robustness and accuracy in models under variably different agricultural conditions [29] . This will help in meeting these challenges as a means of extending models' applicability and reliability under variables of farming.

## 6. Conclusion

The proposed paper presents a hybrid deep learning model using the combination of EfficientNetB0, InceptionV3 with linear regression, enhancing scalability and efficiency and further enhancing the accuracy in the crop yield prediction process. Hybrid models integrate traditional statistical methods with deep learning techniques to resolve challenges in handling big data and further provide stable and high-accuracy performance; hence, the proposed hybrid framework is highly useful in agriculture-based forecasting. The main contributions involve a robust prediction framework that enhances the accuracy and computational efficiency, thus fitting real-world agricultural applications at large scales. This research scope has a very high practical relevance to farmers, agricultural policymakers, and technology developers. This hybrid framework will easily adapt to various agricultural environments, giving proper yield forecasts that help in the efficient use of resources, optimization of crop management, and decision-making support in agricultural planning. Such a methodology would contribute toward sustainable farming and could improve food security by making better crop health and yield predictions. Future work, building upon the present contributions, will incorporate additional data sources, including drone imagery and

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| corn | 0.94 | 1.00 | 0.97 | 76 |
| rice | 0.98 | 1.00 | 0.99 | 130 |
| wheat | 1.00 | 0.94 | 0.97 | 121 |
| accuracy | | | 0.98 | 327 |
| macro avg | 0.97 | 0.98 | 0.98 | 327 |
| weighted avg | 0.98 | 0.98 | 0.98 | 327 |

Figure 15. Classification Report for the InceptionV3 and EfficientNetB0 Hybrid Model

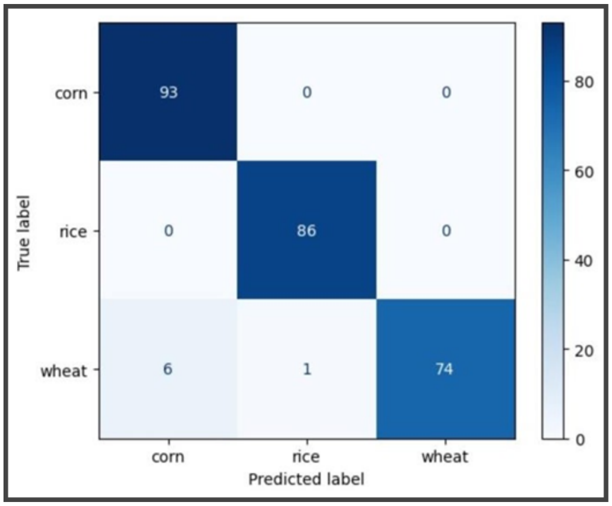


Figure 16. Confusion Matrix for the NASNetMobile with CNN and CSTM Hybrid Model

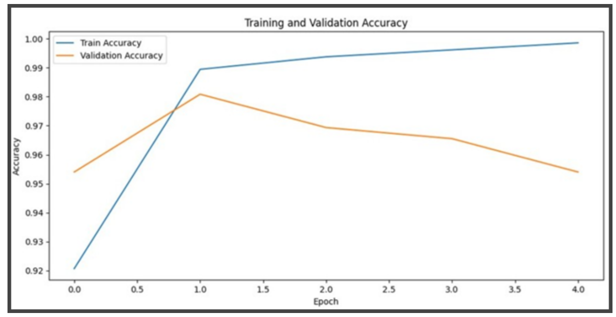


Figure 17. Training and Validation Accuracy Graph for the NASNetMobile with CNN and CSTM Hybrid Model

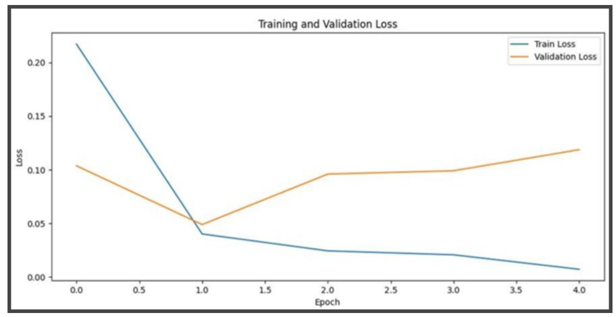


Figure 18. Training and Validation Loss Graph for the NASNetMobile with CNN and CSTM Hybrid Model

soil health data, to further advance predictive performance, while considering advanced learning techniques such as semi-supervised learning that would alleviate data limitations. Applications of the hybrid model for immediate use in real-world agricultural systems can therefore foster data-driven approaches toward resource management and improvement in agricultural productivity.

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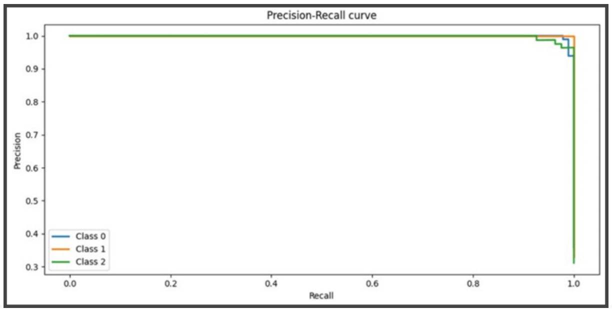


Figure 19. Precision-Recall Curve for the NASNetMobile with CNN and CSTM Hybrid Model

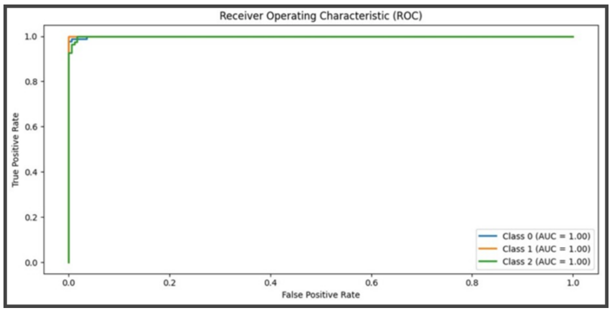


Figure 20. Receiver Operating Characteristic (ROC) Graph for the NASNetMobile with CNN and CSTM Hybrid Model

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| | precision | recall | f1-score | support |
|---|---|---|---|---|
| corn | 0.94 | 1.00 | 0.97 | 93 |
| rice | 0.99 | 1.00 | 0.99 | 86 |
| wheat | 1.00 | 0.91 | 0.95 | 81 |
| accuracy | | | 0.97 | 260 |
| macro avg | 0.98 | 0.97 | 0.97 | 260 |
| weighted avg | 0.97 | 0.97 | 0.97 | 260 |

Figure 21. Classification Report for the NASNetMobile with CNN and CSTM Hybrid Model

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