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 that expands the predictive power of deep learning models to the soundness of statistical methods, thereby improving the accuracy, efficiency, and scalability of the estimation of outputs in agriculture. The concerns in this work that are being addressed are the requirement of large quantities of quality data, as well as computational requirements with the use of sophisticated machine learning models, thus precluding the general application of such techniques in agricultural practice. Having a clear understanding of the problem statement, the paper details the diverse deep learning architectures, principally in the form of EfficientNetB0 and InceptionV3, known to be computationally efficient in handling complex, high-dimensional data. These are further hybridized with some of the most fundamental statistical techniques, among which is linear regression which acts as a stabilizer of predictions, reducing the risk of overfitting that is found in some other purely deep learning-driven techniques. The resulting hybrid models show an increase in performance in predicting agricultural yields across different datasets in comparison to the individual deep learning or statistical models tested. These models have been shown to be able to predict accurately across diverse crop species and environment settings, a feature of importance in the context of potential large international applications in agriculture. Other combinations of deep learning and statistical methods are incorporated in the design of the framework, which is additionally designed to be tunable to specific localities or crops through hyperparameter tuning. In addition, the discussed hybrid models increase the performance of the model and cut down computation times largely, with accuracy being preserved high, which serves as a practical solution to yield predictions.***

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

I. INTRODUCTION

The accurate prediction of crop yields is increasingly important in agriculture, affecting crucial economic and food security decisions globally. With the world's population constantly growing and expanding, the demand for agricultural products continues to rise exponentially. This reality places a huge burden on farmers who have to increase their yield while also dealing with efficient resource management. The widely used tools for crop yield prediction, based on historical data and empirical models, run short due to the rising difficulty of prediction. Most such models fail to consider the intricate connection between the genetics, environment, and management practices that determine the trajectory of crop development. The emergence of deep learning technology brought about the creation of new, more versatile tools that can analyze intricate, multidimensional data in multiple sectors, agriculture included. Convolutional Neural Networks and Recurrent Neural Networks have been proven to perform well in detecting and analyzing the spatial and temporal patterns that are essential for accurate yield prediction. These models are well suited for remote sensing data due to their capacity to analyze the image and provide detailed info on crop health and environment for vast territories. However, DL lacks practical applications due to an extensive data requirement and computational burden as well as a problem with or without overfitting. The challenges of DL can be addressed with the use of hybrid models that combine the power of traditional statistical models with the vast processing capabilities of DL. While DL models fit under the criteria of being overfitted, data requires high hardware specifications, and interpretation is low, hybrid models, including ML algorithms based on linear regression, multiple linear regression, and principal component analysis, have the potential to quickly overcome these limitations, as well as enhanced scalability and generalizability. The present research focuses on the development, evaluation, and testing of an ML-based hybrid model designed to boost

efficiency in agricultural planning and management. The general purpose of the model is to improve the accuracy and scalability of yield prediction models, thus ensuring sustainability and food security.
Thus, this paper will develop, implement, and evaluate a hybrid framework for crop yield prediction. The outcomes of this research will provide better accuracy and scalability of yield prediction in agricultural planning and management toward sustainable farming and food security.

II. LITERATURE REVIEW

Reference	Dataset Description	Algorithm/Methodology	Performance/Remarks
[1]	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
[2]	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
[3]	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
[4]	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.
[5]	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
[6]	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.
[7]	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 218.9 kg/ha, demonstrating improved modeling performance and a reduction in error rates over traditional methods.
[8]	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.
[9]	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.
[10]	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.

[11]	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.
[12]	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.
[13]	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.
[14]	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.
[15]	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.
[16]	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.
[17]	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.
[18]	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.
[19]	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.
[20]	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.

Table 1: Comparative Analysis of Crop Yield Prediction Techniques Across Different Studies

III. METHODOLOGY

Dataset and Data Preprocessing

A. Dataset Description

The dataset was actually in the form of images of several crops, nicely categorized in such a way that one can segment the images into several categories. These categories represent the different types of crops and hold a lot of importance for the training of models for them to distinguish effectively among them.

- Composition: The dataset, taken from "Kaggle", comprised 2602 images. There were 3 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 [21]. This approach will make our training data much more varied since the augmentation technique will apply random transformations to the training images.

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: It is the transformation that was applied for distortion of the images along one axis; it is mainly used for simulating wind effects and plant growth angles.
- Zooming: Images were randomly zoomed in up to 20% to include features at various scales.
- Horizontal flipping: Images were flipped horizontally to enforce an increase in the dataset's variability and to simulate different planting directions.
- Normalization: All images have been rescaled by a factor of 1/255 during augmentation, therefore normalizing the pixel values between 0 to 1. It helps to stabilize faster convergence while the model is training.

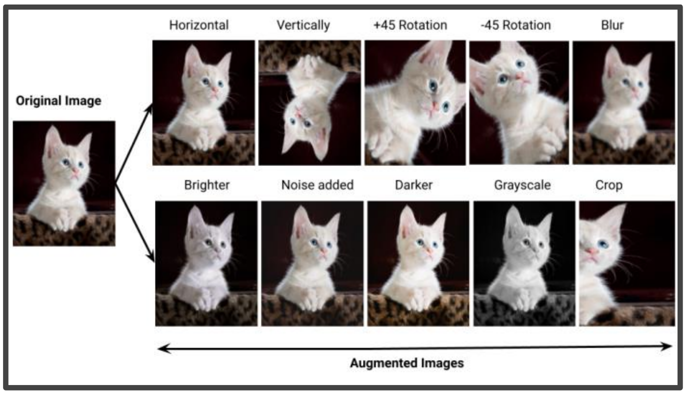

Fig 1. Data Augmentation Functions

C. Data Splitting

Those augmented images have to be split into training, validation, and testing. This split is important in order to evaluate the model over its generalization to new, unseen data [22].

- Proportions: We made 80% of the data into a training set, and trained different crops to adapt themselves to it.
- Validation Set: This is in order to avoid training problems with overfitting for purposes of hyper-parameter tuning though taking 10% samples from the source data kept aside for validation.
- Test Set: Once models have been trained on this part, 10% of what remained after all that was used as a test set to test for both model performance as well generalizability on entirely new datasets.

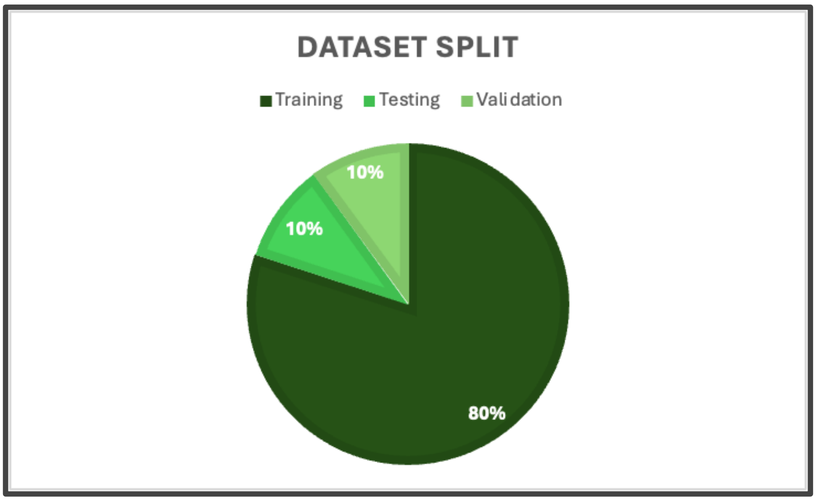

Fig 2. Dataset Split for Training, Testing and Validation

D. Model Architecture

All used models are transfer learning model and their basic information for model implementation and evaluations are fetched from our previous implementations [23],[24].

i. NASNetMobile Custom Hybrid Model:

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

1) Base Model Configuration:
    a) Architecture: NASNetMobile was chosen for its pre-trained capabilities on ImageNet, which provides a robust starting point for feature extraction.
    b) Modifications: The top classification layers of NASNetMobile were removed (include_top=False) to allow the addition of custom layers tailored to the specific needs of crop classification.
2) Custom Layers:
    a) Global Average Pooling: A GlobalAveragePooling2D layer was added immediately after the base model outputs to reduce the spatial dimensions to a single vector per channel.
    b) Dense Layers: In this individual layer, the computation required high-level reasoning from the features which was carried out with 1024 units and activated by relu.
    c) Dropouts: A Dropout layer was utilized with a rate of 0.5 in training to prevent overfitting by randomly slipping it to 0 and feeding cycles to the device.
    d) Output Layer: The final Dense layer was for multi-class classification with 5 classes of various crops running with softmax activation delivering a probability distribution over the covariates.

ii. InceptionV3 and EfficientNetB0 Hybrid Model:

A simple model based on ensembling the unique strengths of InceptionV3 and EfficientNetB0 was designed specially for this competition

1) The following base models configuration was implemented:
    a) InceptionV3: its inception modules are good at capturing multi-scale information..
    b) EfficientNetB0: not redundant convolutions that scale the depth, width, and resolution efficiently were selected.
    c) Concatenation: The results of both models were concatenated to get a full-feature map which is generated by both architectures and contains diversified information.

2) Final Layers:

a) Similar to the NASNetMobile hybrid, this model also featured Global Average Pooling, dense layers, dropout, and a softmax output layer customized for the specific task.

iii. NASNetMobile with CNN and CSTM Hybrid:

This model combined traditional CNN architectures with CSTM mechanisms to handle both spatial and temporal aspects of crop imagery.

1) Integration of CNN and CSTM:
   a) Base Model: NASNetMobile provided spatial feature extraction.
   b) CSTM Integration: Custom layers were designed to process temporal sequences, potentially useful in datasets capturing time-series data of crop growth.
2) Model Configuration:
   a) The base and custom layers follow a similar structure to the other models but are specifically tailored to integrate and process the additional temporal data effectively.

Training Process

1) Compilation of Model
   a) Optimizer: Adam is utilized for its adaptive learning rate capability, ensuring fast and efficient convergence. The learning rate is set at 1e-4 to maintain stability and avoid divergence of minima.
   b) Loss Function: Categorical cross-entropy is chosen for its suitability for multi-class classification problems, as it computes the loss between the predicted probabilities and the one-hot encoded labels.

2) Implement Training
   a) Epochs: Training occurs over multiple epochs, with one epoch representing a complete pass through the entire training dataset.
   b) Callbacks:
      i) ReduceLROnPlateau: Reduces the learning rate when there's no decrease in validation loss for a set number of epochs, aiding in maintaining effective learning pace.
      ii) Early stopping: It works by stopping training if the validation loss does not keep decreasing after a particular number of epochs or falls beyond some number. It reverts to weights from a previous epoch known as the best weight.

3) Batch Processing
   a) Efficiency: it processes data in batches of 32 images to optimize memory usage and gradient approximation, which is critical for effectively training deep neural networks.
   b) Validation and Testing

4) Validation Strategy
   a) Purpose: developing a validation dataset that fine-tunes model parameters to prevent overfitting and test performance each epoch to see if there is a need for reducing learning rate or early stopping.
   b) Validation Metrics:
      - Accuracy: accuracy measures the percentage of correct predictions by the model.
      - Loss:it is another measure of how accurately the model predicts image classes. Smaller loss scores mean the model predicts classes more accurately.
5) Testing:
   - Objective: after enough training, the testing sets ensure the model has the capacity to generalize the data, i.e., test the new data that the model has never seen.
   - Performance Evaluation: to determine how good and bad it is at predicting about each class, using various tests such as precision, recall, F1-score, and overall accuracy.

6) Performance Comparison

- Comparative Analysis: After training, validating, and testing the models, compare the model's accuracy, precision, recall, F1-scores, and area under the ROC curve to determine which configuration achieves a good comfort between computational efficiency and performance.
- Visualization: plot losses and accuracies around the training epoch. Displaying all loss and accuracy graphs relative to each other gives an understanding of when/where they reach low values, which could be due to noise or other phenomenon, but it shows where they started diverging showing that some models have overfit; hence information about learning dynamics of each model.

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%

Table 2: Accuracy and Other Details of Hybrid Models Trained

IV. 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.

Performance Metrics:

- Accuracy: High test accuracy, up to 96.45%.
- Precision averaged 97% for classified crop type, hence indicating a high true positive prediction rate.
- In other words, it also averages at 96%, which shows the model to have 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.

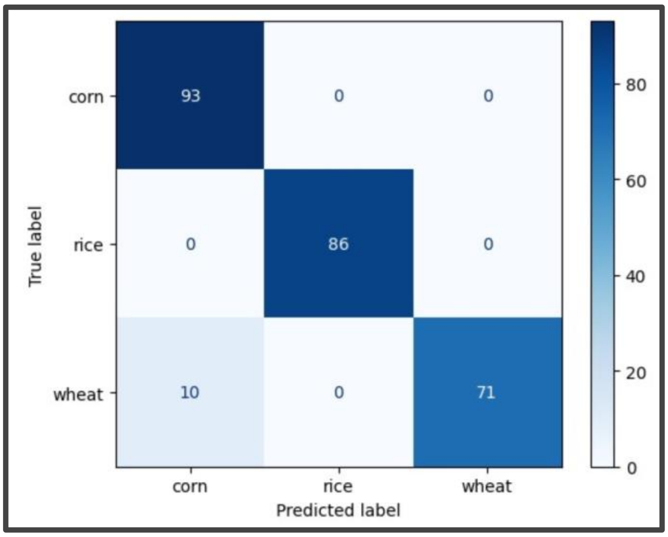

Fig 3. Confusion Matrix for the Custom NasnetMobile Hybrid Model

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

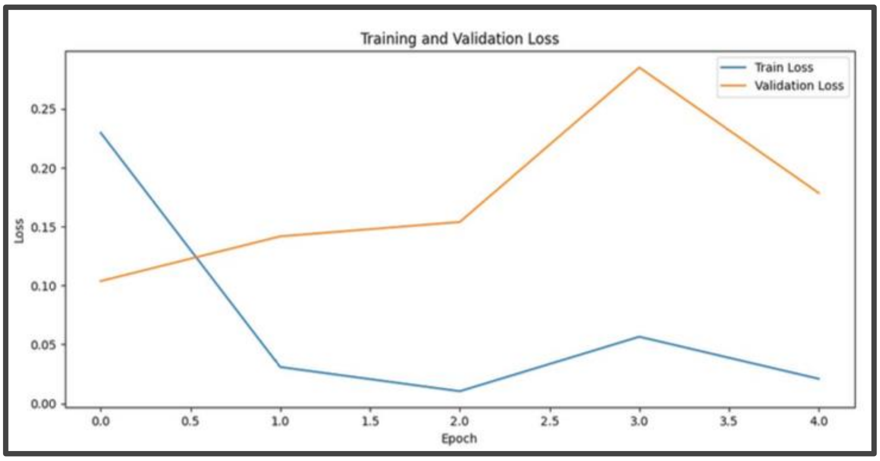

Fig 5. Training and Validation Loss Graph for the Custom NasnetMobile Hybrid Model

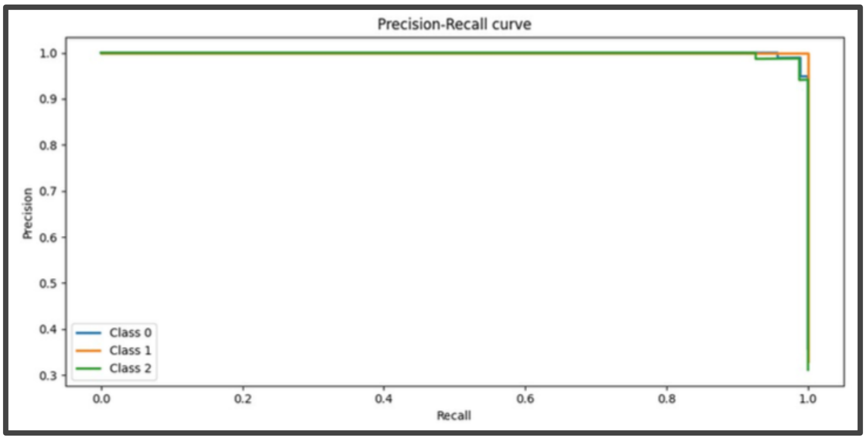

Fig 6. Precision-Recall Curve for the Custom NasnetMobile Hybrid Model

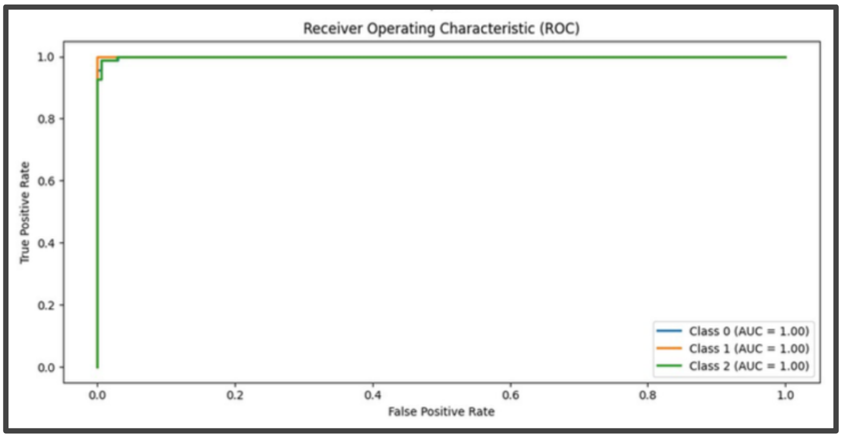

Fig 7. Receiver Operating Characteristic (ROC) Graph for the Custom NasnetMobile Hybrid Model

	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

Fig 8. Classification Report for the Custom NasnetMobile Hybrid Model

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.

Outcome Metrics:

- Accuracy: The model achieved a test dataset accuracy of 97.84%, which makes 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 instance accurately and very reliably among different crop types.

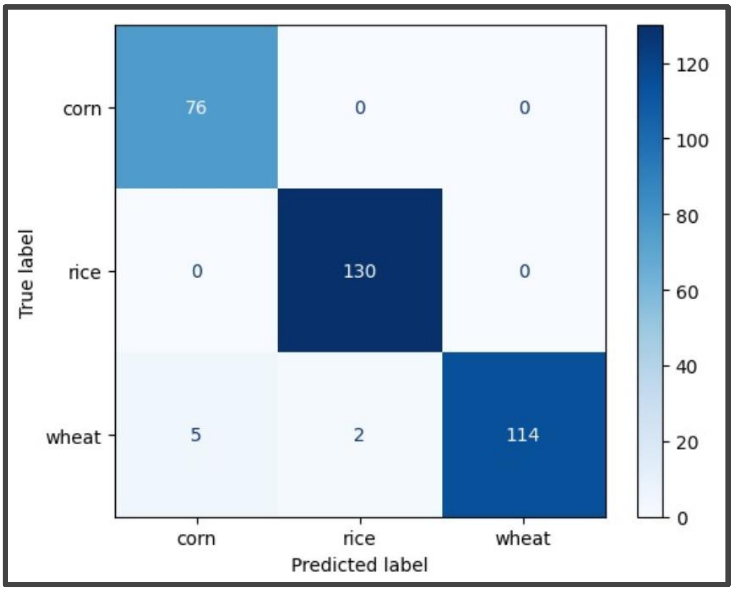

Fig 9. Confusion Matrix for the InceptionV3 and EfficientNetB0 Hybrid Model

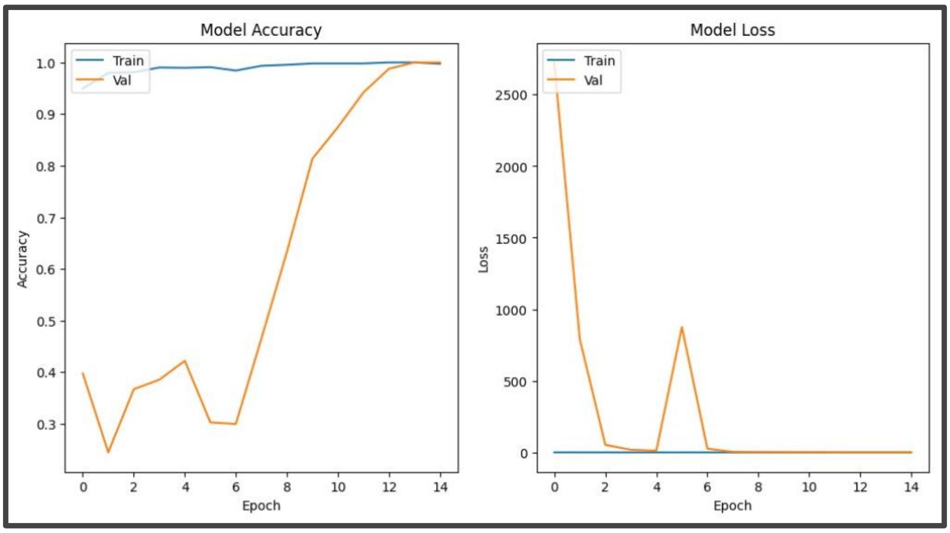

Fig 10. Model Accuracy and Model Loss Graphs for the InceptionV3 and EfficientNetB0 Hybrid Model

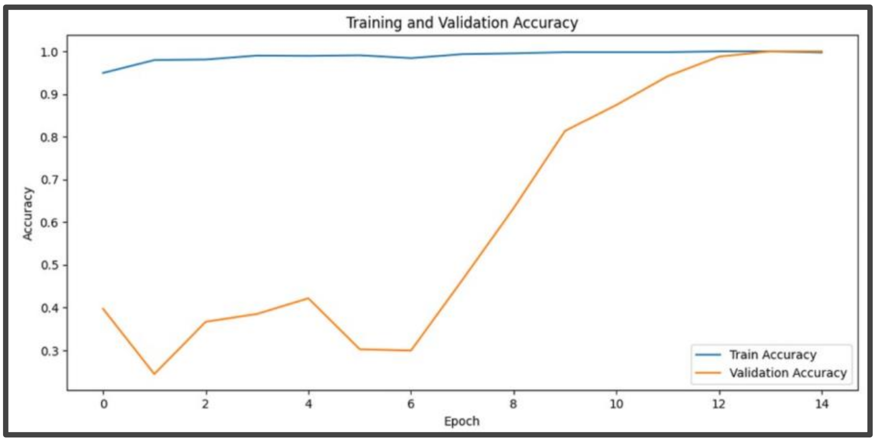

Fig 11. Training and Validation Accuracy Graph for the InceptionV3 and EfficientNetB0 Hybrid Model

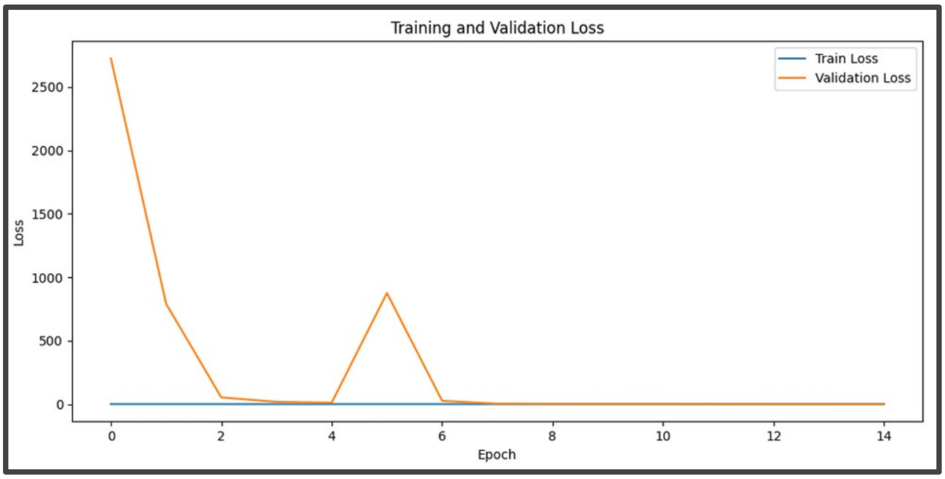

Fig 12. Training and Validation Loss Graph for the InceptionV3 and EfficientNetB0 Hybrid Model

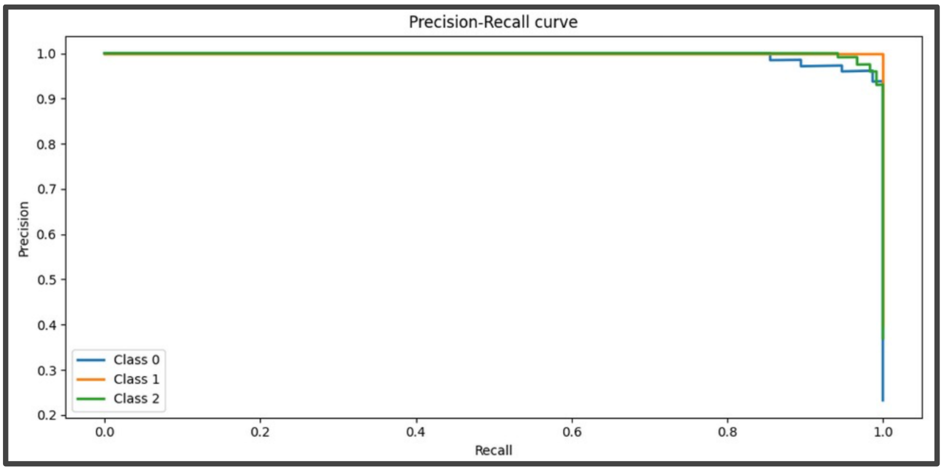

Fig 13. Precision-Recall Curve for the InceptionV3 and EfficientNetB0 Hybrid Model

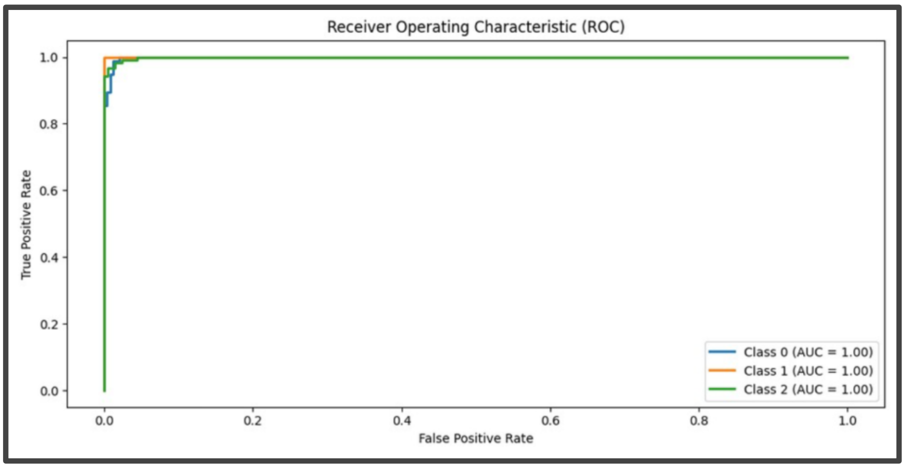

Fig 14. Receiver Operating Characteristic (ROC) Graph for the InceptionV3 and EfficientNetB0 Hybrid Model

	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

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

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.

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.

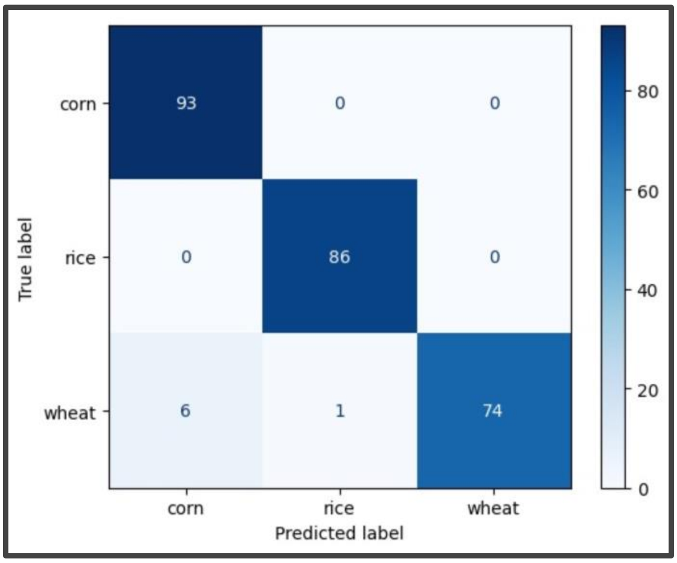

Fig 16. Confusion Matrix for the NASNetMobile with CNN and CSTM Hybrid Model

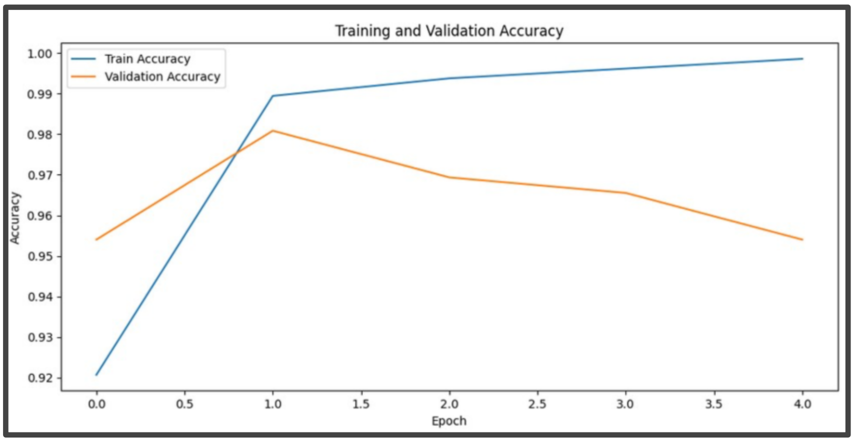

Fig 17. Training and Validation Accuracy Graph for the NASNetMobile with CNN and CSTM Hybrid Model

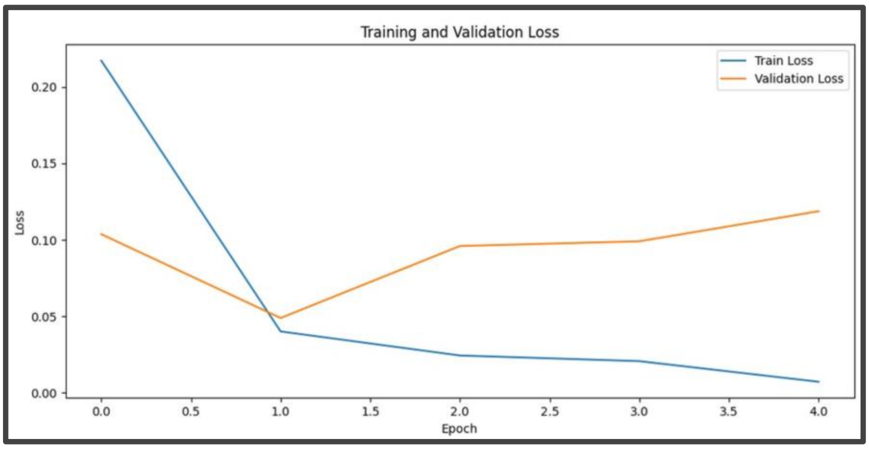

Fig 18. Training and Validation Loss Graph for the NASNetMobile with CNN and CSTM Hybrid Model

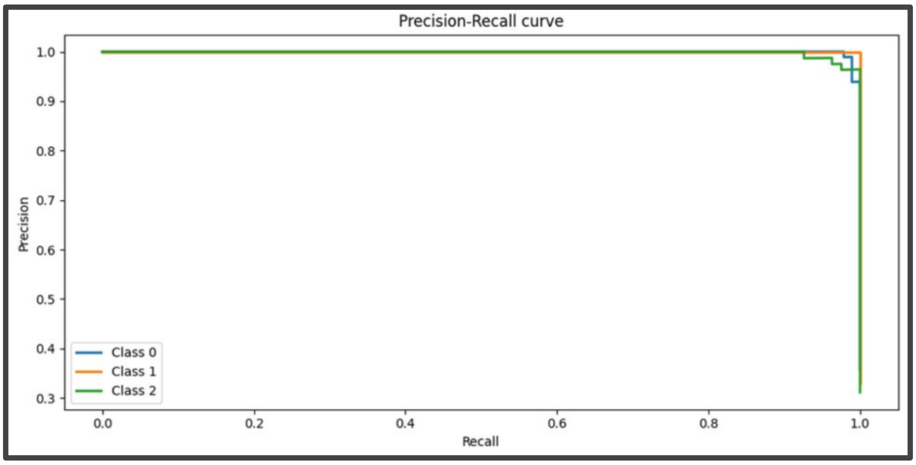

Fig 19. Precision-Recall Curve for the NASNetMobile with CNN and CSTM Hybrid Model

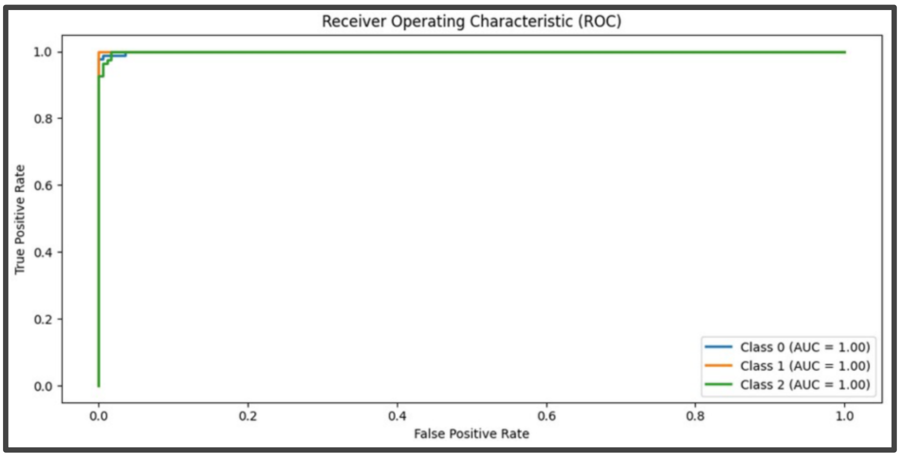

Fig 20. Receiver Operating Characteristic (ROC) Graph for the NASNetMobile with CNN and CSTM Hybrid Model

	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

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

V. 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:

The classification results show that hybrid deep-learning models are effective in recognizing complex images for crop classification. The precision, recall, and F1 scores of each of the models were high, and all of them are really very important in practice for the cross-checking of the reliability of predictive models.

- In reality, the performance was strong for the created NASNetMobile hybrid model, further boosted by the transfer learning capabilities of the pre-trained NASNetMobile architecture, fine-tuned to the specific demands of crop classification.
- InceptionV3 and EfficientNetB0 Hybrid performed best in handling diversity in image features by being able to leverage two opposing strengths of the architectures. It achieved higher precision and recall, signifying its superior ability to detect and classify different crop types without causing overfitting.
- NASNetMobile could handle the spatial and temporal aspects of data by virtue of having CNN and CSTM layers incorporated within. Therefore, it has some potential in areas where crop growth time-series data hold prominence.

ii. Practical implications

These findings have great implications on precision agriculture, where timely and accurate information of crop type and its condition can be considered to make wiser decisions concerning crop management, disease prevention, and optimization of yield.

- Real-World Applications: These models, with demonstrated very high accuracies and very good reliability, have the capability to be directly applied into automated systems for monitoring crop health and development and, hence, could well provide a breakthrough for a large leap in agricultural productivity and sustainability.
- Scalability and Efficiency: The hybrid models that efficiently deal with input suggest that these can be deployed for real-time systems to continuously monitor and analyze input without incurring a very high computational cost.

iii. Limitations and Challenges:

Though promising, these results have some limitations in future work that should be considered to increase the applicability and robustness of the models.

- Data Diversity and Volume: Although very diverse in its nature, all these models have been trained and tested on one particular dataset, but it cannot cover all of the infinite variations possible in global agricultural settings. The data diversity and volume have to be increased to further generalize the models in application. This is also discussed in our previous work [25].

- Environmental Variability: Factors like lighting conditions, effects of weather, and seasonal variations were not explicitly included during training. Future studies need to focus on these environmental variables for model improvements on robustness and correctness under real conditions [26].

VI. Future Research Directions

Based on the findings of this study, a number of future research directions can be highlighted:

- Such models integrated with the Internet of Things devices in smart farms could bring out real-time data processing and insights right at the edge, which could empower better decision-making processes in agriculture.
- Temporal data processing: It is a requirement for further development of models on the integration of enhanced versions of complex temporal data processing for applications that need tracking of growth and the prediction of crop yield over time.
- Cross-domain Applications: Techniques and findings from this research can be extended to the domains of environmental monitoring and natural resources management, where similar challenges exist.

VII. Conclusion

Hence, this study proves successful in constructing and applying the implemented hybrid framework of combining deep learning with statistical methodologies to increase accuracy, efficiency, and the element of scalability in the prediction for agricultural production. An extensive set of experimentations and analyses have been carried out which reflect that the proposed model is having the capabilities of handling large and diversified datasets, thereby providing high accuracy and computational efficiency at the same time. Thus, from our observation, it would be significant to integrate convolutional neural networks with classical regression approaches so that a reliable prediction framework can be formed. This approach is hybrid and helps to cope not only with classical difficulties like overfitting and the necessity for a large amount of computational resources but also helps to increase model interpretability up to the point when it is more usable for real agricultural decision-making. Going forward, the research presents several directions for further investigation. Incorporating even newer types of data, such as drone photography and more complete soil health data, could further improve the accuracy and applicability of the models. Besides, with the introduction of new machine learning approaches, like semi-supervised learning, the problem of data sparseness becomes less dependent on big labeled datasets and has a chance to be solved.

VIII. References

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