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Deep Learning Approaches for Multiclass Crop Classification in Smart Agriculture

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Abstract:- In the context of smart agriculture, enhanced yield prediction and optimal resource management depend heavily on the precise and effective classification of crops. In order to assess and analyze the effectiveness of various deep learning models, such as VGGNet, Sequential, Artificial Neural Network (ANN), and ResNet50. In this work , We a wide range crop picture datasets are process and classify by utilizing these models in order to determine the best method for multiclass crop classification. To guarantee accuracy and resilience, our approach includes exacting preprocessing methods, model training, and validation. The findings show the relative advantages and disadvantages of each model, underscoring the potential of deep learning to transform agricultural practices by precisely identifying and monitoring crops for its ill-health.

Keyword- Deep learning, Multi-class classificatios, CNN, smart agriculture

I.Introduction

Since agriculture is the foundation of many economies, technological developments in order to increase agricultural output and management are constantly needed. Crop categorization using traditional approaches, which rely on human observation and standard algorithms, is frequently labour-intensive, time-consuming, and error-prone. A new frontier has developed with the introduction of deep learning, which offers advanced methods for more accurately and efficiently evaluating and classifying crop photos.

The paper [1] presents a novel approach to weed detection and classification by combining Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. This hybrid model aims to enhance the accuracy and efficiency of identifying and classifying weeds in agricultural fields, a crucial task for precision agriculture. The paper[2] introduces an innovative approach for agricultural spraying using unmanned aerial vehicles (UAVs). The proposed method leverages vision-based adaptive variable rate spraying to optimize pesticide and fertilizer application. This technique aims to improve the efficiency and effectiveness of spraying operations in precision agriculture. The paper [3], focuses on a novel approach for classifying chili leaf diseases using a customized version of the EfficientNetB4 deep learning model. By leveraging advanced neural network architectures, the authors aim to enhance the precision of multiclass classification tasks for different chili leaf diseases based on image data. The paper[4] by Mona Tahmasebi and Mohammad Gohari introduces a significant advancement in agricultural robotics by combining autonomous operation with a color-based vision system for pesticide spraying. This approach promises improved precision and efficiency in pesticide application, which can benefit modern farming practices.

Convolutional Neural Networks have become the cornerstone of image classification tasks due to their ability to capture spatial hierarchies in data. Key studies, such as those by [5] and [6], demonstrated the effectiveness of CNNs in image classification, which has been adapted for crop classification. Recent research[7], shows that CNN architectures like AlexNet, VGGNet, and ResNet are effective in distinguishing between various crop types based on remote sensing imagery. Transfer learning leverages pre-trained models on large datasets to improve performance on specific tasks with limited data. Research by [8] and [9] has demonstrated that transfer learning can significantly enhance crop classification accuracy. Models such as InceptionV3 and DenseNet, pre-trained on datasets like ImageNet, have been fine-tuned for crop classification tasks in studies like [10]. RNNs and LSTMs are used to capture temporal dependencies in sequential data. While traditionally used for time-series data, studies such as [11] have explored their application in crop monitoring where temporal data from satellite imagery is analyzed. This approach has been less common but shows promise in integrating temporal aspects with spatial data for comprehensive crop classification

In this work, four deep learning models—VGGNet19, Sequential, Artificial Neural Network (ANN), and ResNet50—are used and their performance matrices are assessed. These models are excellent choices for agricultural applications because of the nature of crop image. Creating a real-time crop classification system that can correctly identify various crop types from visual data is the main goal of this work. This improve crop classification accuracy and speed by incorporating aforesaid deep learning models and assist farmers and other agricultural stakeholder. Better decision-making, resource allocation, pesticide spraying and crop management are all anticipated benefits of this work, which will ultimately boost agricultural sustainability and efficiency.

.This study uses an extensive dataset of crop images for the models' rigorous training, validation and testing. Various image pre-processing steps are to maximize the models' efficiency and guarantee their resilience in a variety of scenarios. By comparing different models, we can better understand their advantages and disadvantages, which will guide our future research and development in the field of smart agriculture. This study, would help to show how deep learning methods can revolutionize the agricultural industry and open the door to creative solutions that meet the industry's expanding needs.

II. Methodology

The initial stage of this study was gathering and preparing a large dataset of crop images that were divided into three groups. Various pre-processing methods were applied to make sure that models could handle variability and generalize effectively. These included standardizing pixel values, scaling images to a consistent size, and adding transformations like flips, shifts, rotations and image augmentation to the image dataset. Preprocessing measures of this types were essential for improving the robustness and quality of the image dataset.

VGGNet, Sequential, Artificial Neural Network (ANN), and ResNet50 deep learning models were chosen for comparison. These models were selected because they have a track record of successfully managing challenging image categorization jobs. Every model has a distinct set of advantages; for example, VGGNet is well known for its deep architecture, but ResNet50 addresses the vanishing gradient problem with its residual learning framework.

The 16-layer VGG16 form of VGGNet, which is well acclaimed for its picture recognition accuracy produced promising result. With several convolutional and pooling layers, the Sequential model was specially constructed to extract and learn hierarchical information from the crop photos. Despite having a simpler structure, the ANN model's feedforward network design served as a benchmark for comparison. With 50 layers, ResNet50 maintained gradient flow by using residual connections, enabling deeper networks without degrading.

The pre-processed dataset was used in a rigorous training process for every model. To reduce the likelihood of overfitting and improve training effectiveness, we adjusted the hyperparameters of the models and used strategies like learning rate scheduling and early stopping.

In order to provide a thorough evaluation of these models' performance in categorizing the three crop classes, metrics like accuracy, precision, recall, and F1-score were employed. This comparison study shed light on the advantages and disadvantages of each model, directing future developments and possible practical uses in smart agriculture.

III. Results and Discussion

The crop image data set is divided into training set and a testing set for the study purpose. The models were trained on the training set, and their performance and capacity to correctly categorize the crop photos was assessed on the testing set. Three different crop varieties that were chosen from farmers' fields and photographed using a regular camera were the subject of investigation. Four deep learning models—VGGNet, Sequential, Artificial Neural Network (ANN), and ResNet50—were assessed for performance. The ImageNet dataset was used for pre-training each model, and our crop image dataset was used for further fine-tuning.

In our tests, the 50-layer version of the ResNet50 model showed excellent accuracy in categorizing the crops, with an average classification accuracy of 89.3%. The performance of the model was greatly improved by the application of transfer learning, which made it possible for it to quickly and efficiently adjust to the unique features of our agricultural dataset. We used a 16-layer network called VGG16 for this investigation, and it produced an amazing 97.8% average classification accuracy. The depth and simplicity of VGG16's architecture made it a solid option for our application, yielding dependable and consistent outcomes.



Fig 1: Crop Class 1 Fig 2:Crop Class 2 Fig 3:Crop Class 3

Although they were also examined, the Sequential model and ANN performed far worse. The accuracy of the ANN was 83.2%, compared to 85.6% for the sequential model. These outcomes demonstrated how well more sophisticated architectures, such as VGG16 and ResNet50, handled the complicated characteristics of crop images.

While VGG16 had the best accuracy (97.8%), there were times when it was unable to accurately forecast the class of some crop photos. However, ResNet50 proved its resilience and dependability by accurately predicting the class of every input image with an accuracy of 89.3%.

ResNet50 produced more consistent results across all classes, even though VGG16 displayed the best accuracy. These results highlight the significance of choosing a model according to the particular accuracy and dependability criteria in practical crop categorization applications for smart agriculture. Below plot shows various performance parameters shown by all models used in this study.

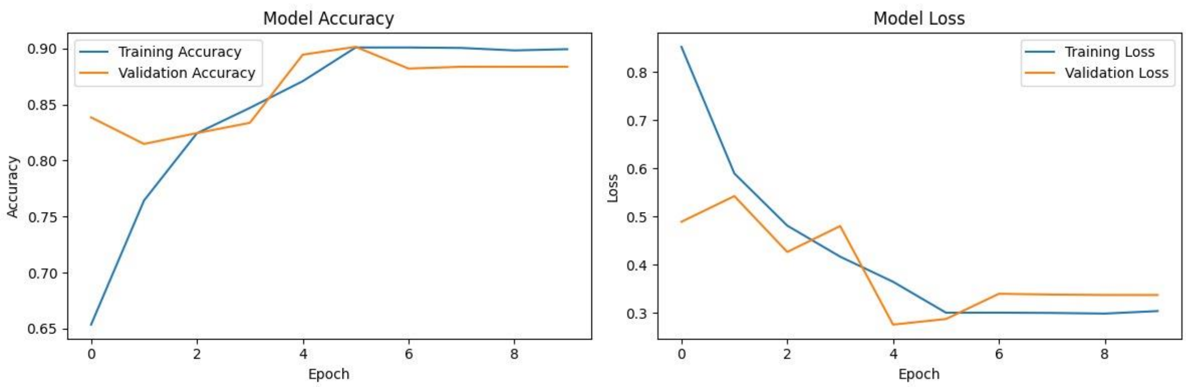

Fig 4: Model accuracy and loss for ResNet50 pre-trained model.

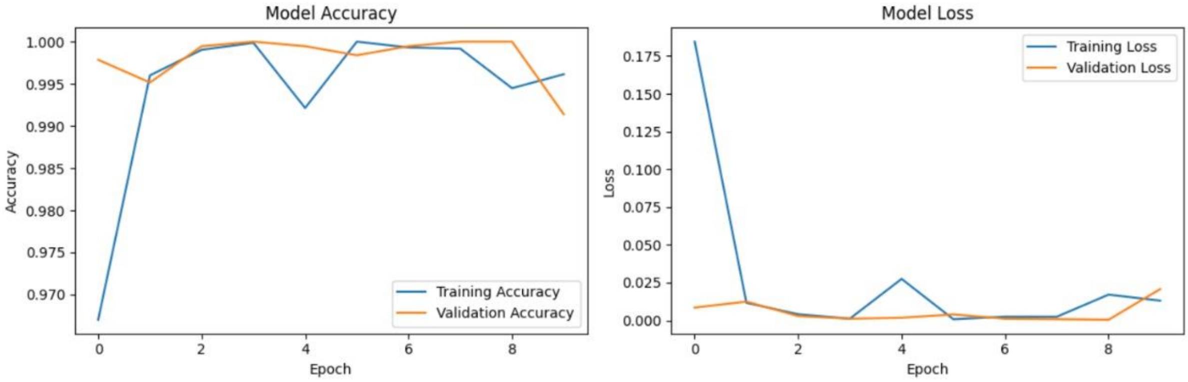

Fig 5: Model accuracy and loss for VGG16 pre-trained model.

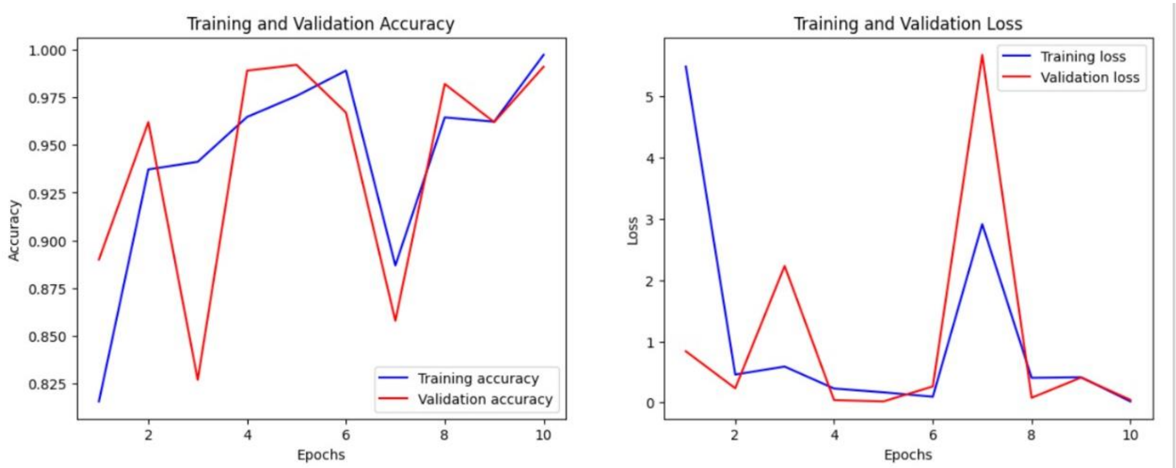

Fig 6: Model accuracy and loss for ANN pre-trained model.

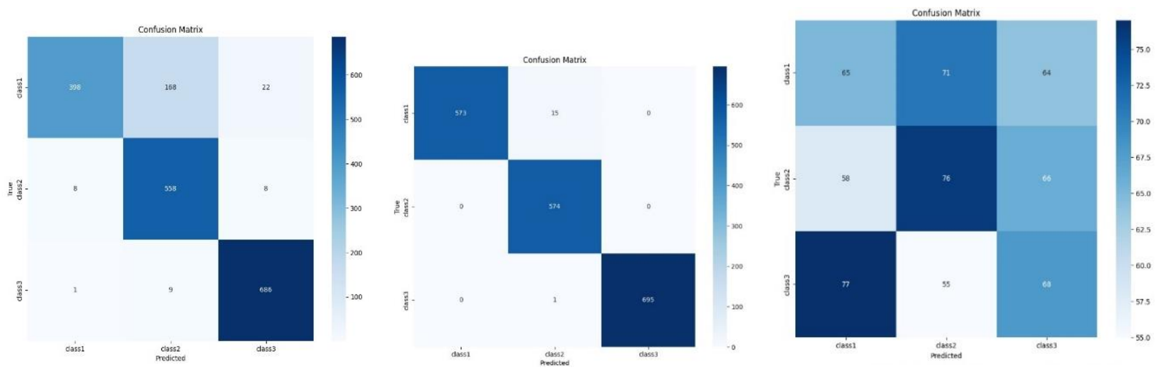

Fig 7: Confusion matrix a) Resnet50 b) VggNet19 c) ANN model

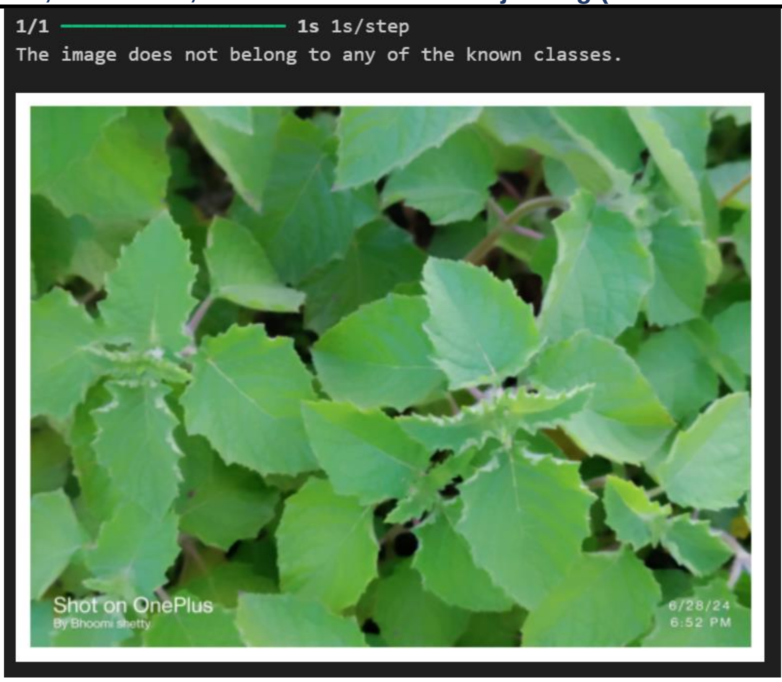

Fig 10: Query image to predict the image which is not in the dataset.

IV Conclusion

In this work, an automatic identification method for crop images taken straight from the farmers field using deep learning techniques. The goal is to incorporate deep learning techniques to increase the precision of crop classification and pesticide application, hence promoting sustainable agriculture. Multiclass crop classification systems have the ability to improve pesticide application accuracy by applying treatments only to crops that need them and efficiently. This development helps to promote more ecologically friendly farming methods while also optimizing the usage of resources. Deep learning technology offers farmers a useful tool that helps them to apply pesticides more efficiently and encourages better crop management.

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