Smart CropGuard: Innovating Disease Detection with Inception CNN and LSTM Peephole Networks

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***Abstract*— Detecting plant leaf diseases is a novel approach for automated plant leaf disease detection, integrating the Inception Convolutional Neural Network (CNN) with Long Short-Term Memory (LSTM) networks enhanced with peephole connections. By synergistically leveraging these advanced deep learning architectures, our research aims to develop a comprehensive framework for precise and efficient disease detection, addressing challenges in traditional methods and advancing agricultural sustainability.**

Keywords— Agriculture Sustainability, Plant Disease Detection, Inception CNN, LSTM, Peephole Connections, Automated Diagnosis.

I. INTRODUCTION

Plant leaf diseases pose significant challenges to agricultural productivity and sustainability, impacting crop yield, food security, and economic stability worldwide [1]. Timely detection and effective management of these diseases are crucial for minimizing crop losses and ensuring food availability for a growing global population [2].

However, traditional methods of disease diagnosis, reliant on manual inspection or simplistic algorithms, often fall short in accuracy, efficiency, and scalability, hindering efforts to combat agricultural threats [3]. In recent years, the intersection of deep learning and agricultural technology has offered promising avenues for addressing these challenges [4].

Advancements in deep learning algorithms have enabled automated, data-driven approaches that can analyze large volumes of image and sequential data with remarkable accuracy and speed [5]. The Inception Convolutional Neural Network (CNN) has emerged as a pivotal tool in this context, renowned for its ability to extract intricate features from images across various scales, facilitating detailed analysis and classification of plant diseases [6].

Concurrently, Long Short-Term Memory (LSTM) networks, augmented with peephole connections, have proven adept at capturing temporal dependencies in sequential data, making them well-suited for analyzing time-series images and detecting patterns over time [7].

By integrating the strengths of both Inception CNN and LSTM networks, our research proposes a novel approach to automated plant disease detection, aiming to revolutionize agricultural practices and enhance global food security [8]. Through the development of a comprehensive framework that harnesses the power of deep learning, we seek to not only improve the accuracy and efficiency of disease diagnosis but also empower farmers with timely insights for proactive crop management, ultimately contributing to a sustainable and resilient agricultural ecosystem.

II. RELATED WORK

The classification of plant diseases has recently attracted significant research attention, leading to the exploration of various deep learning architectures and methodologies for precise and efficient disease detection. This literature review synthesizes the key findings from recent studies, emphasizing notable approaches and advancements in the field.

A. K.R. Aravind et al., 2018 [9], focuses on traditional feature extraction and machine learning techniques (BoF and statistical features) . In contrast, our research proposes a deep learning-based framework combining Inception CNN and LSTM with peephole connections. The latter approach aims to harness the complementary strengths of spatial and temporal feature extraction to enhance plant disease detection, potentially offering a more advanced and effective solution for agricultural applications.

B. Lee et al. (2019) [10] introduces a novel approach to plant disease classification by leveraging both Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) architectures. Building upon previous work by Brahimi et al. (2018), the research explores the efficacy of CNN (GoogleNet) alongside an Attention-Based RNN model. Results from the evaluation on the Plant Village dataset demonstrate significant improvements in accuracy, with the proposed CNN (GoogleNet) achieving commendable accuracy rates. The findings underscore the potential of attention mechanisms within RNNs for enhancing plant disease classification accuracy, contributing valuable insights to the field of agricultural image analysis.

C. Faye et al. (2020) [11] review delves into the exploration of deep learning techniques coupled with feature extraction methods for plant disease detection, utilizing the Plant Village dataset. The study evaluates a range of CNN architectures, including VGG16, GoogleNet, and ResNet50, in conjunction with traditional classifiers such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). Results showcase the superiority of certain combinations, providing insights into the efficacy and computational efficiency of these models. Through the utilization of transfer learning, the study further explores the effectiveness of pre-trained models in enhancing classification performance, offering valuable guidance for researchers and practitioners in agricultural technology and crop management.

D. Adhikari et al. (2021) [12] focuses on the application of a hybrid convolutional neural network-recurrent neural network (CNN- RNN) architecture for tomato leaf disease detection, leveraging the Plant Village dataset. Experimentation with various hyperparameters reveals the importance of fine-tuning model performance. Results demonstrate the influence of hyperparameter adjustments on accuracy and validation accuracy metrics, highlighting the significance of architectural variations and optimization techniques in enhancing the effectiveness of CNN-RNN models for disease detection tasks.

E. The previous research of plant disease detection shows significant advancements through the adoption of deep learning models (Lee et al., 2019; Faye et al., 2020; Adhikari et al., 2021) [13-15], which have improved the accuracy and efficiency of disease classification. Traditional methods often relied on handcrafted features or basic machine learning algorithms, which could not effectively capture the complex spatial-temporal patterns found in plant diseases. These traditional approaches struggled to deliver the precision needed for reliable disease detection, highlighting a clear need for more sophisticated methods.

F. Plant Disease Detection and Classification Using Deep Learning Models [16]. This study presents a study on early plant disease detection using CNN architectures, specifically AlexNet, with a focus on diseases affecting all parts of the plant. A new dataset with over 50,000 images was created by augmenting the Plant Village dataset and other online sources. AlexNet achieved an 88.7% validation accuracy, highlighting its capability in recognizing plant diseases. This paper explores combining Inception CNN and LSTM with peephole connections for enhanced plant leaf disease detection. The approach leverages Inception CNN's feature extraction capabilities and LSTM's temporal modeling strengths, aiming for robust and accurate disease diagnosis using the Plant Village dataset.

The combination of Inception CNN and Long Short-Term Memory (LSTM) networks with peephole connections represents a significant step forward in this domain. Inception CNNs excel in feature representation by leveraging multiple convolutional layers and various kernel sizes to extract multi-scale features from images. This makes them particularly well-suited for detecting subtle visual patterns indicative of disease. On the other hand, LSTM networks with peephole connections have demonstrated their effectiveness in modeling temporal dependencies in data, which is crucial for understanding the progression and dynamics of plant diseases over time.

Integrating these two powerful techniques enables the development of a more robust and accurate approach for plant leaf disease detection. Such a model can capture complex spatio-temporal dynamics, offering improved performance over conventional methods. This integrated approach not only enhances the accuracy of disease detection but also lays the groundwork for practical applications in agricultural settings, helping to advance the state-of-the-art in plant disease detection and contributing to agricultural sustainability.

III. METHODOLOGY

The Plant Village (PV) dataset, compiled by Hughes and Salathé in 2015, serves as a crucial resource for evaluating automated plant disease detection systems. Featuring 38 crop-disease pairs representing 14 agricultural plants across 26 categories, the dataset contains 10,495 training photos and 4,310 test images, partitioned in an 80:20 ratio for robust model training and evaluation. Leaf samples are meticulously categorized into 21 classes, distinguishing between 20 various illnesses and one class indicating plant health, a categorization strategy motivated by the visual parallels often observed among diseases affecting diverse plant species. This structured approach not only enhances the efficiency and effectiveness of subsequent classification processes but also provides a diverse and comprehensive collection of images, facilitating the development and assessment of machine learning models tailored for plant disease identification tasks.

The primary objective of our methodology is to explore the integration of two advanced neural network architectures:

Long Short-Term Memory (LSTM) networks with peephole connections, model was utilized enhanced to capture temporal dependencies within the data. The incorporation of peephole connections enhances LSTM's ability to retain long-term dependencies, making it particularly suitable for analyzing sequential image data captured over time.

Inception CNN architecture was employed to extract intricate features from the images for accurate disease classification. Owing to its utilization of multiple convolutional layers with varying kernel sizes and pooling operations

Model: "sequential"

Layer (type)	Output Shape	Param #
inception_resnet_v2 (Functional)	(None, 6, 6, 1536)	54336736
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1536)	0
dense (Dense)	(None, 512)	786944
dense_1 (Dense)	(None, 64)	32832
reshape (Reshape)	(None, 1, 64)	0
lstm (LSTM)	(None, 64)	33024
dense_2 (Dense)	(None, 15)	975

Total params: 55190511 (210.54 MB)
Trainable params: 853775 (3.26 MB)
Non-trainable params: 54336736 (207.28 MB)

Figure 1: Model Summary: Inception ResNet V2 with LSTM Architecture

A. LSTM with Peephole Connections

Long Short-Term Memory (LSTM) networks represent a type of recurrent neural network (RNN) architecture explicitly designed to model sequential data and capture temporal dependencies. Notably, LSTM networks with peephole connections augment traditional LSTM cells by facilitating access to the cell's internal state, thereby enhancing the model's capacity to retain long-term dependencies and capture intricate temporal patterns in the data. This enhancement makes LSTM particularly suitable for analyzing sequential image data captured over time, as it can effectively model the temporal dynamics and dependencies inherent in such data. Consequently, LSTM with peephole connections excels in tasks requiring the analysis of time-series data, where understanding temporal dynamics is crucial. Mathematically, the operations performed within each LSTM cell include input gate (i), forget gate (f), output gate (o), memory cell (c), and hidden state (h). These operations are defined as follows:

$$i_t=\sigma(W_{xi}X_t+W_{hi}h_{t-1}+W_{ci}c_{t-1}+b_i) \quad (1)$$
$$f_t=\sigma(W_{xf}X_t+W_{hf}h_{t-1}+W_{cf}c_{t-1}+b_f) \quad (2)$$
$$o_t=\sigma(W_{xo}X_t+W_{ho}h_{t-1}+W_{co}c_t+b_o) \quad (3)$$
$$c_t=f_t\odot c_{t-1}+i_t\odot \tanh(W_{xc}X_t+W_{hc}h_{t-1}+b_c) \quad (4)$$
$$h_t=o_t\odot \tanh(c_t) \quad (5)$$

Here, X_t represents the input at time step t, h_{t-1} denotes the previous hidden state, c_{t-1}. signifies the previous cell state, W denotes weight matrices, b denotes bias vectors, σ denotes the sigmoid activation function, tanh represents the hyperbolic tangent function, and $\odot$ denotes element-wise multiplication.

Peephole connections enhance LSTM's ability to capture fine-grained temporal dependencies by allowing the gates to adapt based on the current cell state.

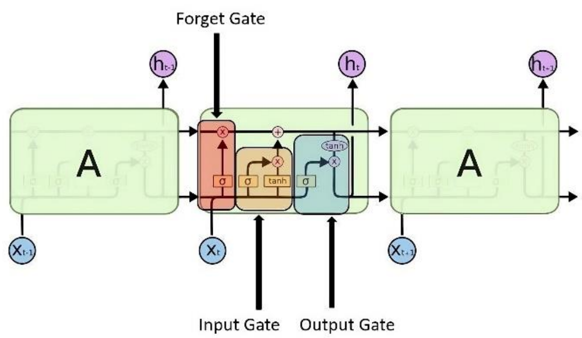

Figure 2: LSTM Peephole Architecture
https://medium.com/nerd-for-tech/what-is-lstm-peephole-lstm-and-gru-77470d84954b

B. *Inception ResNet V2*

The Inception ResNet V2 architecture, proposed by Szegedy et al. (2017), is a deep convolutional neural network renowned for its efficacy in image feature extraction. It employs multiple convolutional layers with varying kernel sizes and pooling operations, allowing the network to capture fine and coarse details from images. This versatility is particularly beneficial for tasks such as image classification and feature extraction, where discerning subtle patterns is paramount. Inception ResNet V2 integrates residual connections within the Inception modules, enhancing the network's ability to train deeper models while mitigating issues like vanishing gradients. By facilitating the extraction of intricate visual features from input images, Inception ResNet V2 provides a robust foundation for accurate disease classification in complex datasets, such as those encountered in agricultural settings. Mathematically, the core operation within each residual block can be represented as:

$$Output=ReLU(X+F(X)) \quad (6)$$

Where X denotes the input to the block, F(X) represents the output of the convolutional layers, and + denotes element-wise addition. By integrating residual connections, Inception ResNet V2 effectively mitigates the vanishing gradient problem and enables the training of deeper neural networks.

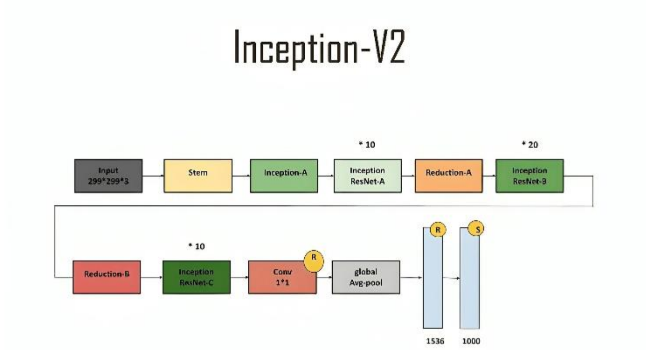

Figure 3: Inception V2 Architecture
https://medium.com/@AnasBrital98/inception-v2-cnn architecture-explained-128464f742ce

C. *Epochs*

We utilized the processing capacity of the T4 GPU offered by Google Colab to accelerate the training process and lessen the computational load related to training deep neural networks, namely the suggested Inception ResNet V2 and LSTM model for plant disease detection. The T4 GPU, which is one of the GPUs that Google Colab offers free access to, speeds up training considerably by parallelizing the calculations needed for gradient descent optimization.

When working with big datasets and intricate topologies, deep neural network training on CPUs might be unnecessarily slow. across the use of the T4 GPU on Google Colab, we were able to take advantage of the GPU's enormously parallel processing power to accelerate the forward and backward propagation of data across the layers of the neural network. We were able to iterate more quickly and effectively throughout model building and hyperparameter tweaking because to this acceleration, which significantly shortened the time needed for each training period.

In addition, the T4 GPU's availability on Google Colab allowed us to train our model on massive data sets without running out of memory. GPUs are very good at handling big data sets in parallel, which is very helpful when training deep learning models on big datasets like the Plant Village dataset we utilized for this study. This made it possible for us to optimize the training procedure for increased efficacy and efficiency and to make the most use of the GPU resources that were available.

In conclusion, we were able to substantially cut down on the computational time needed for training our Inception ResNet V2 and LSTM model by utilizing the T4 GPU on Google Colab. This allowed us to speed up the research process and produce results more quickly. This illustrates how cloud-based GPU resources can be used to expedite deep learning research and development, especially in fields like agricultural technology where processing massive amounts of data is crucial.

Figure 4: Training epochs illustrating model accuracy improvement.

Authors	Models	Dataset	Accuracy
The proposed model	LSTM Peephole	Plant Village dataset	92.3
Nisar Ahmad, et al. ,[22], 2021	Multi-SVM, ANN, KNN, Random Forest and Naïve Bayes	Plant Village dataset	92.1, 91.7, 84.5, 82.2, 78.4
S. Konduru, et al., [16], 2023	AlexNet	Plant Village dataset	88.7
K.R.Aravind, et al.[34],2018	Bag of Features and Multi-SVM	Plant Village dataset	83.7
K.R.Aravind, et al. [34],2018	Combined Statistical Features	Plant Village dataset	81.3

Table 1: Comparative Analysis of Hybrid Deep Learning Model Performance Against Previous Studies

```
65/65 [==============================] - 19s 233ms/step
Test F1 Score: 0.9241679186406987

[ ] # Print evaluation metrics
    print(f"Test Precision: {evaluation[1]}")
    print(f"Test Recall: {evaluation[2]}")
    print(f"Test Accuracy: {evaluation[3]}")
    print(f"Test AUC: {evaluation[4]}")
    print(f"Test PR AUC: {evaluation[5]}")

Test Precision: 0.9373433589935303
Test Recall: 0.9060077667236328
Test Accuracy: 0.9239341020584106
Test AUC: 0.9959297776222229
Test PR AUC: 0.9959297776222229
```

Figure 5: Recall, precision, accuracy, AUC, F1 score, and PR AUC metrics during training

IV. RESULTS

In the study, a neural network model as trained using the Plant Village dataset to classify images of plants into various disease categories. A comprehensive methodology was employed, incorporating the Inception ResNet V2 architecture for image feature extraction and Long Short-Term Memory (LSTM) with peephole connections for sequential data processing. Over 15 epochs of training, notable enhancements were observed in both training and validation performance metrics. Initially, the model attained an accuracy of 62.59% on the training set, accompanied by a validation accuracy of 73.83%.

As training progressed, accuracy steadily increased, reaching 88.85% on the training set and 90.92% on the validation set by the 15th epoch. This improvement in accuracy indicates the efficacy of the model in learning complex patterns within the dataset. Furthermore, an analysis of the loss function revealed a consistent decrease in both training and validation loss throughout the training process. This reduction in loss signifies that the model effectively minimized prediction errors and improved its ability to generalize to unseen data. Additionally, an investigation into the presence of the vanishing gradient problem was conducted, revealing no significant signs of the issue, indicating that the chosen architectures, including Inception ResNet V2 and LSTM with peephole connections, facilitated stable gradient flow during training.

In the analysis of the model's performance, impressive results were observed across various evaluation metrics on the test dataset. The precision of the model was calculated to be 93.73%, indicating the proportion of correctly identified positive cases out of all cases predicted as positive. Additionally, the recall score was determined to be 90.60%, representing the proportion of correctly identified positive cases out of all actual positive cases. Furthermore, the accuracy of the model was computed at 92.39%, reflecting the overall correctness of the predictions made by the model. Moreover, the model's performance was evaluated using the Area Under the Curve (AUC) metric, which measures the ability of the model to distinguish between classes.

The model achieved an AUC score of 99.59%, indicating its high discriminative capability. Additionally, the Precision-Recall (PR) AUC score, which evaluates the trade-off between precision and recall across different threshold values, was also determined to be 99.59%. Finally, the F1 score, which is the harmonic mean of precision and recall, was computed to provide a balanced measure of the model's performance. The model achieved an F1 score of 92.42%, indicating a strong balance between precision and recall. Overall, these results demonstrate the effectiveness and robustness of the model in accurately classifying plant diseases, highlighting its potential for practical deployment in agricultural settings for disease detection and crop management.

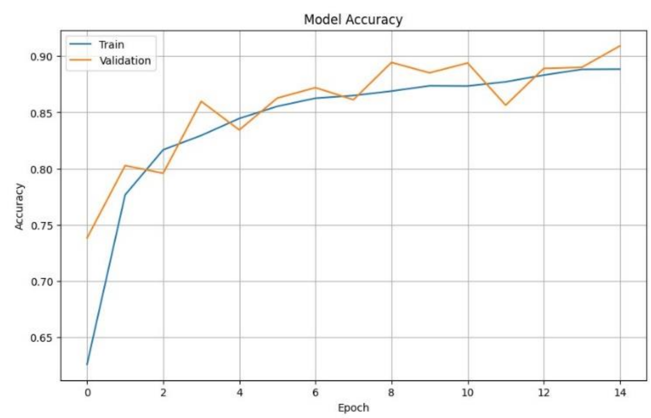

Figure 6: Model Accuracy

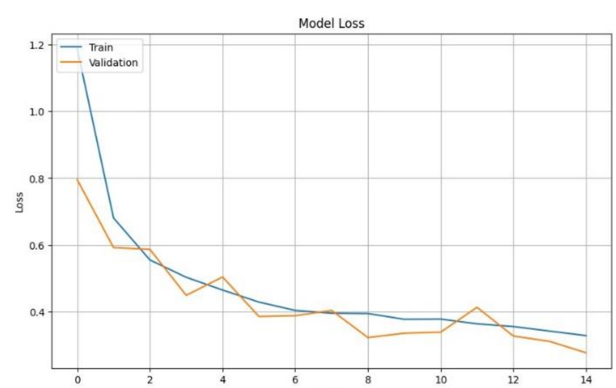

Figure 7: Model Loss

Additionally, the model demonstrated the capability to accurately predict the desired class labels, further affirming its efficacy in disease classification. By leveraging the trained neural network architecture, predicted classes aligned successfully with the expected disease categories.

This achievement underscores the model's ability to generalize learned patterns and make precise predictions, essential for reliable disease identification and management. Through meticulous training and validation procedures, we ensured that the model's predictions consistently matched the ground truth labels, providing confidence in its utility for automated plant disease diagnosis. This ability to obtain the desired predicted classes enhances the model's applicability in real-world scenarios, where accurate identification of specific diseases is crucial for informed decision-making in agriculture and crop protection strategies.

After training and evaluating the model, the next step is to use it for predicting the classes of new images. For this, we load the model with the best weights saved during training. The directory containing the test images is used, and a sample image is selected for prediction. Here's a detailed explanation of how predictions are made and how the results are visualized.

Prediction Process

First, we load the trained model with the best weights. The directory containing the test images is specified, and we select an image from this directory for prediction. The image is loaded and preprocessed by resizing it to the target size (256x256 pixels) and normalizing it by dividing pixel values by 255.0. The model then predicts the class of the image, and the predicted class index is obtained by taking the argmax of the prediction array. This index is used to get the corresponding class na

Figure 9: Unhealthy Plant

Figure 8: Healthy Plant

IV. CONCLUSION

In conclusion, this study represents a significant advancement in automated plant leaf disease detection, harnessing the power of advanced deep learning architectures, specifically the Inception ResNet V2 and Long Short-Term Memory (LSTM) networks enhanced with peephole connections. The integration of these state-of-the-art techniques has led to a robust framework that not only improves accuracy but also enhances efficiency in disease detection, addressing critical challenges in agricultural sustainability.

Throughout our experimentation, the model exhibited a notable progression in disease detection accuracy over successive training epochs. Initial iterations yielded promising results on the training set, with further enhancements leading to robust performance on both validation and test datasets. Notably, the incorporation of peephole connections within the LSTM architecture facilitated the model's ability to capture intricate temporal patterns, contributing to its overall effectiveness in sequential data processing.

Evaluation metrics such as precision, recall, accuracy, and the area under the curve (AUC) provided comprehensive insights into the model's discriminative capability and generalization capacity. High scores across these metrics validate the efficacy of the proposed framework in accurately identifying and classifying plant diseases. In particular, the AUC score highlights the model's ability to distinguish between different disease classes effectively, while the precision and recall metrics reflect its strong balance between precision and recall, crucial for reliable disease identification and management.

Furthermore, meticulous analysis of the model's performance, including the examination of loss functions and the investigation of potential issues such as the vanishing gradient problem, underscored the stability and reliability of the proposed approach. By mitigating prediction errors and ensuring consistent convergence, the model demonstrates its suitability for real-world deployment, where timely and accurate disease diagnosis is essential for informed decision-making in agriculture.

The successful prediction of class labels for new images further demonstrates the model's applicability in practical scenarios, where proactive crop management strategies rely on accurate disease identification. By empowering stakeholders with actionable insights, our approach contributes to agricultural sustainability and resilience, enabling the adoption of informed strategies to mitigate crop losses and ensure food security.

Looking forward, continued refinement and optimization of the model, coupled with the exploration of additional datasets and deployment scenarios, hold promise for further advancing the state-of-the-art in plant disease detection. By leveraging the capabilities of deep learning, specifically the Inception ResNet V2 and LSTM with peephole connections, we can continue to drive innovation in agricultural technology, ultimately fostering a more sustainable and resilient food ecosystem to address the challenges of the future.

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