Multi-Channel Multi-Modal Concatenation-based Deep Learning Model for Leaf Infection and Soil Property Prediction

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Abstract. One of the most important tasks in improving crop yield quality is accurately predicting leaf infection and its related soil properties. A Multi-channel Convolutional Neural Network (MCNN) was already designed that utilized a separate channels for learning features of soil and leaf infection images. But, it was not able to capture the spatiotemporal variance of the leaf infections and may lose data because of feature fusion at the decision stage. Hence, this article proposes a Multi-channel Multimodal Concatenation-based CNN with Long Short-Term Memory (M^2C^2NN-LSTM) model to improve the generalizability of feature learning for leaf infection and soil property prediction. At first, the MCNN architecture is built to learn the deep features from soil and leaf images together using DenseNets followed by the Convolutional LSTM (ConvLSTM), which helps to extract the spatiotemporal dependencies between them. During feature learning, three different types of concatenation strategies are employed to fuse the encoding of spatiotemporal features with better generalization ability and achieve robust prediction. Once the prediction process is completed, the predicted outcomes of leaf infections and related soil properties are broadcasted to the cultivators via smartphones to develop yield productivity. At last, this model is validated by the different categories of leaf infection and soil photos for cotton, pineapple, and strawberry crops plants. The testing outcomes demonstrate that the M^2C^2NN-LSTM attains a mean accuracy of 90.3% for leaf infection prediction and 91.85% for soil property prediction than the conventional classifiers.

Keywords: Leaf infections, Soil properties, Multi-channel CNN, LSTM, Multi-modal fusion, Feature learning.

1 Introduction

Crop infections are regarded as one of the most important variables impacting cultivation, being crucial for a major fluctuation in plant morphological or commercial efficiency and, in certain cases, becoming a constraint to this effort. To minimize output risk and ensure food security,

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pathogen monitoring and control strategies must be implemented correctly, focusing on frequent harvest inspections along with early and precise pathogen detection. These are the techniques that phytopathologists encourage the most [1].

On the other hand, the proper detection of the signs of various plant pathogens is the most difficult problem for farming systems [2]. Classical farming techniques cannot handle huge portions of farms or facilitate critical early feedback to decision-making strategies due to physical and automated processes.[3].

An area of artificial intelligence called machine and deep learning algorithms [4] seems to be very successful at identifying and categorizing images. Farming has embraced these algorithms for different purposes, like leaf infection recognitiInitially, photos of leaves and soil were taken and forwarded to a server through the Internet of Things (IoT) systems [5]. The leaf photos were used to extract textural features and contour-based shape descriptors. Color histogram-based characteristics were also retrieved from soil photos. Then, SVM used these features to predict plant leaf disease. But, SVM has a high training burden when using large-scale datasets since it was not able to manage a larger number of features. To solve this problem, the deep learner is used to forecast plant leaf disease, which doesn't demand domain expertise. To recognize crop leaf infections with significant efficiency, several authors have applied well-known Deep CNN (DCNN) structures like AlexNet, VGGNet, InceptionV3, ResNet, DenseNet, and so on [6]. These structures use leaf and soil photos separately for predicting leaf infection. Conversely, both soil and leaf infection images were considered together, which may not improve the prediction performance effectively. Accordingly, an MCNN has been developed that adopts independent channels for soil and leaf infection images [7]. It was based on the fact that the major feature learning by CNN for leaf infection images was being maintained regarding soil images to prevent major data merging among leaf and soil photos.

An M^2C^2NN-LSTM model is proposed to enhance the accuracy of predicting leaf infections and related soil properties. In this model, three different types of concatenation strategies are employed: i) concatenation at the information stage called early concatenation; ii) concatenation at the feature stage called in-between concatenation; and iii) concatenation at the decision stage called late concatenation. Initially, the MCNN structure is constructed to concurrently train the deep features from both soil and leaf images through DenseNets, which are then connected to the ConvLSTM to extract the spatiotemporal dependencies between them. Moreover, different concatenation strategies are used at various stages to merge the encoding of spatiotemporal features with better generalization ability and achieve robust prediction.

2 Literature survey

2.1 Machine learning algortihms for leaf disease detections

The Machine learning based alggortihms for leaf disease detections are providing promising results for small datsets. A novel fuzzy set [8] was designed based on the neutrosophic logic-based partition scheme to analyse the ROI. But, its complexity was high, while increasing the number of images and the fuzzy membership values must be properly chosen to improve the efficiency. A Multi-class SVM (Multi-SVM) [9] was used to categorize the soil images using the linear kernel. But, the dataset was limited, and its training time was high for large-scale datasets. An Adaboost, tree, and Artificial Neural Network (ANN) algorithms [10] was used to classify the various soil types.

2.2 Deep learning and transfer learning algortihms for leaf disease detections

A customized Faster Region-CNN (FRCNN) system [11] was presented for identifying leaf spot infections in sugar beet. Conversely, the CNN hyperparameters must be adjusted to circumvent false categorizations. CNN was suggested [12] for extracting the features from rice leaf infection images. Then, the SVM was applied to categorize and recognize particular infections. In addition, the SVM parameters were optimized using a 10-fold cross-validation scheme. To analyzed different structures of the CNN model to predict and classify vegetable leaf infections [13].

2.3 Limitations of existing works

The ML algorithms had high computational costs and were prone to overfitting issues. However, machine learning algorithm cannot handle large scale datasets. The efficiency of deep learning methods depends on the huge number predefined parameter and number of infection image samples used for training. The performance of transfer learning mainly depend on pre-learned model. The proposed work eliminate the above limitations for leaf disease detections.

3 Proposed methodology

This part explains the M^2C^2NN-LSTM model for leaf infection and soil property prediction. First, different types of crop leaf infection images and soil photos are captured by the camera. Then, such images are transferred to an image processing module via either a wired or wireless system for further analysis. Once all the images are acquired, the noise elimination scheme is used to eliminate the distortions from the photos. These pre-processed photos are provided to MCNN, which facilitates separate channels for soil and leaf infection images. During MCNN training, multi-modal fusion strategies are used to enhance the learning of the feature representations. After learning all deep features from the soil and leaf infection images, these images are passed to the ConvLSTM to learn the spatiotemporal dependencies associated with the leaf infections and their related soil properties. Finally, the fully connected and softmax layers are employed for the final prediction.

3.1 Image acquisition and preprocessing

Primarily, the leaf infection images and their related soil images are captured for 3 major crops: strawberry, cotton, and pineapple. The captured images of leaf infection include bacterial flight, cylindrocladium, mealy bugs, ralstonia solancearum, Rhizoctonia, spider mites, and thielaviopsis. Among them, bacterial flight and mealybug-infected leaf images are only captured for the cotton crop.

3.2 M^2C^2NN-LSTM classifier for leaf infection and soil property prediction

This M^2C^2NN-LSTM model considers the concept of cooperative feature learning. It considers the leaf infection and soil images as inputs and feeds them into 2 individual convolutional dense networks to learn deep feature representation. The convolutional units may considerably decrease the number of learnable variables using the idea of weight sharing, which helps the model solve the overfitting issue. DesneNets adopt shortcut links that execute characteristic representation, therefore efficiently preventing feature attenuation triggered by several combined non-linear conversions. It guarantees that the extracted features preserve the data at the local level, whereas the global features of images are not defined. To solve this problem, such characteristics are passed to the ConvLSTM network linked to the result of the DenseNets to train the spatiotemporal relations among them.

Compared to the standard LSTM, ConvLSTM explicitly considers substituting the input images as the sequential vector multiplication in LSTM gates using convolutional processes, where the photo's transitional representation preserves the spatial relationship data in the repetition

MCNN with ConvLSTM Structure

The MCNN structure has 2 different input channels for leaf infection images and soil photos, correspondingly. The traits associated with all leaf infection and soil photos are concatenated and transferred along the specific channels [7]. The initial level is the convolution unit utilized to traverse along the matrix of the image to generate a primary feature matrix of deep characteristics using an adaptive filter. Such feature maps are then transferred along with the 2nd convolution without pooling. The feature maps created by this unit are given to the flattening unit, which converts this matrix from a 2D to a 1D array since the subsequent layers of the network are dense units. These matrices are provided to the dropout unit for regularization.

The sixth layer of this network is a dense unit that uses the linear operation on the feature maps created by the convolution unit. This dense unit is used to learn the global relationship amid the features and abstraction of more complex pixels in the image

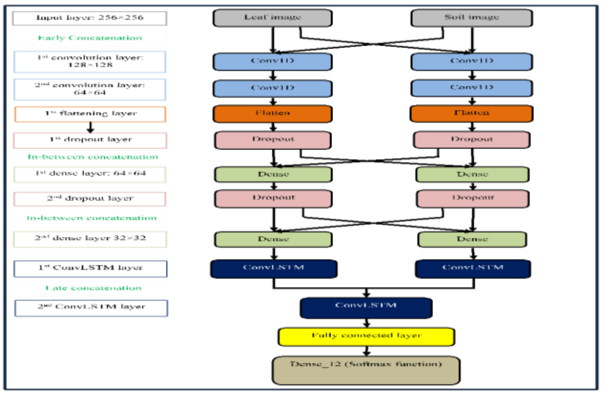

Fig. 1. Structure of M^2C^2NN-LSTM classifier for leaf infection and related soil property prediction

For an input sequence $X_1, \dots, X_N$ and $Y_1, \dots, Y_N$, consider $m_1, \dots, m_N$ are the cell activation states and $h_1, \dots, h_N$ are the hidden states. The ConvLSTM network executes the below operations:

$$i_n = sigmoid(w_i * X_n + U_i * h_{n-1} + b_i) \quad (1)$$

$$f_n = sigmoid\left(w_f * X_n + U_f * h_{n-1} + b_f\right) \quad (2)$$

$$o_n = sigmoid(w_o * X_n + U_o * h_{n-1} + b_o) \quad (3)$$

$$m_n = f_n \circ m_{n-1} + i_n \circ tanh(w_m * X_n + U_m * h_{n-1} + b_m) \quad (4)$$

$$h_n = o_n \circ tanh(m_n) \quad (5)$$

In the above equations, $*$ is convolution function and $\circ$ is element-wise product function. i_n, f_n and o_n are the input, forget and output fates whereas b_i, b_f, b_o and b_m are the biases. The input weights $w_{\sim}$ and hidden weights $U_{\sim}$ denote the learned convolution kernels of the ConvLSTM network.In this work, the outcome from dense units of each channel is fed to the corresponding ConvLSTM networks where the feature map is passed to the ConvLSTM at various intervals. The convolutional kernel spatial dimensions of the input weights and hidden weights are assigned to 3×3 with stride of 1×1. Typically, the outcome of the ConvLSTM unit is spatiotemporal characteristics with the spatial dimension of 7×7, which is similar to that of the ConvLSTM input, while its temporal dimension is decreased to 1.

Multi-modal Concatenation

Feature concatenation is the basic part of leaf infection and soil property prediction. In this work, 3 multimodal concatenation strategies are considered: early concatenation, in-between concatenation and late concatenation. The softmax unit predicts the output-input possibility $P(C_l|X)$ and $P(C_s|Y)$ for all leaf infection and soil property labels $C_{l_{1\le l\le c}}$ and $C_{s_{1\le s\le c}}$, as:

$$P(C_l|X) = \frac{e^{\left(X_{C_l}\right)}}{\sum_{q=1}^{|X|} e^{\left(X_q\right)}} \tag{6}$$

$$P(C_s|Y) = \frac{e^{\left(Y_{C_s}\right)}}{\sum_{q=1}^{|Y|} e^{\left(Y_q\right)}} \tag{7}$$

In Eqns. (6) & (7), X and Y are the resultant feature vector of a given leaf infection and soil images as guided by M^{2}C^{2}NN-LSTM.Remember that, for given the leaf infection and soil observation X and Y, every of the channel generates $P(C_l|X)$ and $P(C_s|Y)$ for all labels $C_{l_{1\le l\le c}}$ and $C_{s_{1\le s\le c}}$, correspondingly. Moreover, a simple linear mixture is performed to determine the final class-membership probabilities for the given X and Y simultaneously as:

$$P(C_l|X) = \varepsilon \cdot P(C_l|X) + (1-\varepsilon) \cdot P(C_l|X) \tag{8}$$

$$P(C_s|Y) = \varepsilon \cdot P(C_s|Y) + (1-\varepsilon) \cdot P(C_s|Y) \tag{9}$$

The coefficient ε controls the contributions of all channels to the prediction. The optimum range of ε is calculated practically. Because for the absolute prediction outcomes, the leaf infection and soil images are allocated the label C^* and C' with the highest output-input possibility as:

$$C^* = \left(P(C_l|X)\right) \tag{10}$$

$$C' = \left(P(C_s|Y\,)\right) \tag{11}$$

Thus, both the leaf infection and the related soil images are predicted concurrently by training each channel of the M^{2}C^{2}NN-LSTM network.

4 Results and discussion

The effectiveness of the presented and existing models is assessed based on various evaluation metrics for predicting leaf infections and soil properties of different crops. In this analysis, various categories of soil photos and their associated leaf infections for cotton, pineapple, and strawberry crops are acquired (discussed in Section 3.1). The efficiency of the M^2C^2NN-LSTM-based leaf infection prediction model is evaluated with the SVM, FRCNN, EfficientNet [19], InceptionResNetV2 [18], and MCNN [7]. Similarly, the efficiency of the M2C2NN-LSTM-based soil property prediction model is evaluated with the Multi-SVM [9], Adaboost [10], Tree [10], ANN [10], and MCNN [7].

4.1 Accuracy

It is the proportion of the True Positives (TP) and True Negatives (TN) to the overall number of samples analyzed.

$$Acc = \frac{TP + TN}{TP+TN+False\ Positive\ (FP)+FalseNegative\ (FN)} \quad (12)$$

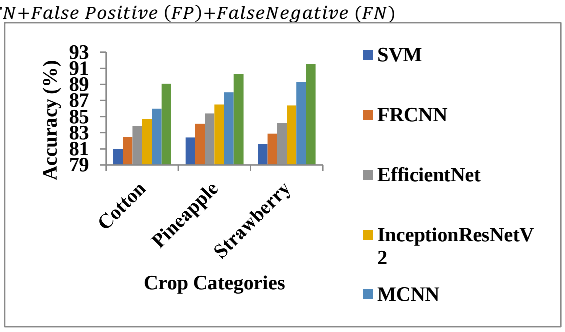

Fig. 2. Accuracy comparison for different leaf infection prediction models

Figure. 2 illustrates the accuracy of various leaf infection prediction models for 3 major crops. It is observed that the accuracy of M^2C^2NN-LSTM for predicting pineapple leaf infections is 9.6%, 7.4%, 5.7%, 4.4%, and 2.6% better than the SVM, FRCNN, EfficientNet, InceptionResNetV2, and MCNN models. Thus, it is realized that the M^2C^2NN-LSTM achieved better accuracy for predicting leaf infections in different crops compared to other models.

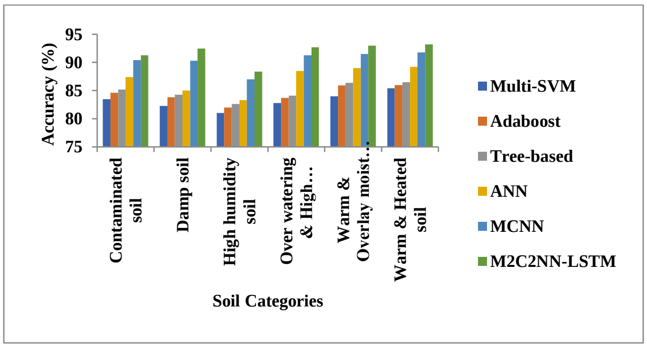

Fig. 3. Accuracy comparison for different soil property prediction models

Figure. 3 illustrates the accuracy of various soil property prediction models for 3 major crops. M^2C^2NN-LSTM outperforms the Multi-SVM, Adaboost, Tree-based, ANN, and MCNN models for predicting high humidity soil by 9.1%, 7.8%, 7%, 6.1%, and 1.6%, respectively. As a result, the M^2C^2NN-LSTM model outperformed other models in terms of predicting the soil properties of different crops.

4.2 Precision

It is the proportion of predicted characteristics that are appropriate and analyzed at the TP rates.

$$Precision = \frac{TP}{TP+FP} \tag{13}$$

It is indicated that the precision of the M^2C^2NN-LSTM for predicting strawberry leaf infections is 11.9%, 10.3%, 8.5%, 5.7%, and 2% larger than the SVM, FRCNN, EfficientNet, InceptionResNetV2, and MCNN models. Therefore, it is realized that the M^2C^2NN-LSTM has better precision compared to other prediction models for all crops.

4.3 Recall

It is the measure of predicting characteristics at TP and FN rates.

$$Recall = \frac{TP}{TP+FN} \tag{14}$$

It is indicated that the recall of the M^2C^2NN-LSTM for predicting the pineapple leaf infections is 9.9%, 6.4%, 5%, 4.4%, and 1% larger than the SVM, FRCNN, EfficientNet, InceptionResNetV2, and MCNN models.

4.4 F-Measure

It is defined by

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{15}$$

It is indicated that the f-measure of the M2C2NN-LSTM for predicting the cotton leaf infections is 10.4%, 7.9%, 6.1%, 5.1%, and 2.3% greater than the SVM, FRCNN, EfficientNet, InceptionResNetV2, and MCNN models.

5 Conclusion

In this paper, the M^2C^2NN-LSTM model was developed to increase the generalizability of feature learning for simultaneously predicting leaf infections and related soil properties. First, the leaf infection and soil images for different crops were collected. The collected images were concatenated at the data level and fed to the corresponding channels. The resultant feature maps were then passed to the ConvLSTM to learn the spatiotemporal dependencies among the images from each channel. After that, the outcomes of each channel were concatenated at the decision level and fed to the softmax unit to get the ultimate prediction. At last, the investigational analysis evidenced that the M^2C^2NN-LSTM model for predicting leaf infection and soil properties achieved maximum performance compared to the other models. The accuracy of M^2C^2NN-LSTM attains a mean accuracy of 90.3% for leaf infection prediction and 91.85% for soil property prediction than the conventional classifiers. This model can be implemented in a cloud server and the images collected from IOT sensors are detected in real-time manner in the future.

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