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APPLICATION OF CONVOLUTIONAL NEURAL NETWORK FOR DETECTING TOMATO LEAF DISEASES

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Abstract: Plant diseases are a common occurrence in the agricultural field, impacting crop productivity. The contribution of the economy to agriculture plays a significant role in enabling effective disease detection. The surveillance of large and diverse crop fields has increased the importance of plant disease detection. Farmers face challenges when transitioning between different disease management approaches. To ensure proper control measures and maintain plant health, timely detection of tomato leaf diseases is crucial. Mechanized techniques and methodologies offer efficient and constructive means of disease detection, reducing the labor-intensive task of surveillance in large-scale cultivation. Early detection of disease symptoms on plant leaves allows for prompt action. This review explores various algorithms used for image segmentation and automated classification in disease detection. It also encompasses different disease classification methods employed in plant disease detection. By employing deep learning technology, the disadvantages of artificial selection of disease spot features can be avoided, making disease feature extraction more objective and enhancing research efficiency and technological advancements. This review provides insights into the recent progress made in deep learning-based crop leaf disease identification, highlighting current trends, challenges, and the integration of advanced imaging techniques. It aims to serve as a valuable resource for researchers studying plant disease and insect pest detection, while also addressing existing challenges and unresolved issues.

Keywords: Plant leaf disease images, disease symptoms, deep learning, artificial selection, disease detection

1.INTRODUCTION

Automated plant disease identification is crucial for enhancing agricultural practices and improving crop yield. Visual identification of diseases on plant leaves can be challenging, especially in large-scale cultivation and remote areas. To overcome these challenges, researchers have explored various solutions, including machine learning algorithms and image processing techniques. Early detection of plant diseases is vital for effective prevention and control, as it plays a crucial role in agricultural management and decision-making. Climate change and global transfer of diseases further emphasize the need for timely and accurate diagnosis. By leveraging techniques such as artificial neural networks (ANNs) and support vector machines (SVMs), coupled with image pre-processing methods, researchers have made progress in disease detection. Computer vision advancements offer opportunities for precise plant protection and expanded applications in precision agriculture. Deep convolutional neural networks (CNNs) trained on diverse plant disease databases have shown promise in accurately distinguishing diseased leaves from healthy ones.

2. LITERATURE SURVEY

De Luna, R.G., Daddios, E.P., & Bandala, A.A. (2019)- Smart farming systems equipped with necessary infrastructure have introduced innovative technologies that greatly enhance agricultural production, including tomatoes. However, tomato plants are prone to diseases influenced by various factors such as environmental conditions, soil composition, and sunlight exposure. To tackle this issue, recent advancements in deep learning and computer systems have paved the way for effective detection of tomato leaf diseases. This study developed a motor-controlled image capturing box capable of capturing images of all sides of each tomato plant, enabling the identification and recognition of leaf diseases. The experiment focused on the Diamante Max tomato breed, and a dataset comprising both diseased and healthy plant leaves was collected. A deep convolutional neural network (CNN) was trained to identify three specific diseases: Phroma Rot, Leaf Miner, and Target Spot. The system utilized a CNN-based approach to determine the presence of these diseases in monitored tomato plants. The trained F-RCNN anomaly detection model achieved a confidence score of 80%, while the Transfer Learning disease recognition model demonstrated an impressive accuracy of 95.75%. When implemented in real-world scenarios, the automated image capturing system achieved a remarkable accuracy of 91.67% in recognizing tomato plant leaf diseases.

Liu, B., Jiang, P., Chen, Y., He, D., & Liang, C. (2018) -This research focuses on the detection of five common types of apple leaf diseases: aria leaf spot, brown spot, mosaic, grey spot, and rust. The study utilizes deep learning techniques to improve the performance of convolutional neural networks (CNNs) in detecting these diseases in apple leaves. The researchers employ the Apple Leaf Disease Dataset (ALDD), which includes complex and laboratory images. By utilizing data augmentation and image annotation technologies, a new detection model is constructed using deep CNNs, specifically the Rainbow concatenation and Google Net Inception structure. The proposed INAR-SSD model is trained using a testing dataset containing 26,377 images of apple leaf diseases, enabling the detection of the five mentioned diseases. Experimental results demonstrate that the INAR-SSD model achieves a detection performance of 78.80% with a high detection speed of 23.13 frames per second (FPS). These findings highlight the effectiveness of the INAR-SSD model as a high-performance solution for early diagnosis of apple leaf diseases, enabling real-time detection with improved accuracy and faster speed compared to previous methods.

Vamsi, K., Sahithya, V. A., Vihari, B. S., Reddy, P. S., & Balamurugan, K. (2017). -This paper aims to enhance the Indian economy by increasing agricultural productivity through the implementation of an efficient and smart farming system. The study focuses on identifying unhealthy leaves using image processing techniques, specifically examining ladies finger plant leaves to detect early stages of diseases like yellow mosaic vein, leaf spot, and powdery mildew. The process involves capturing leaf images, performing image processing operations, segmenting the leaves, extracting features, and classifying them as healthy or unhealthy. The study considers noisy image datasets to account for practical limitations in diverse climatic conditions and terrains. Image segmentation is carried out using K-Means clustering, while SVM and ANN algorithms are employed for classification. Principal Component Analysis (PCA) is used to reduce the feature set. The results show that disease detection accuracy using SVM and ANN algorithms is 85% and 97% respectively, with even higher accuracy rates of 92% and 98% when noise is eliminated. This research contributes to the advancement of complete automation in the agricultural industry, paving the way for more efficient and productive farming practices.

Zhang, Y., Song, C., & Zhang, D. (2015).-This paper presents an improved Faster RCNN algorithm for accurate recognition of crop disease leaves and localization of diseased areas. The focus is on detecting healthy tomato leaves and four specific diseases: powdery mildew, blight, leaf mold fungus, and ToMV. The proposed method incorporates a depth residual network for extracting image features, replacing VGG16 to capture deeper disease features. Additionally, the algorithm employs k-means clustering to enhance the accuracy of bounding box anchoring based on clustering results. The adjusted anchor frame closely aligns with the actual bounding boxes in the dataset. Experimental results reveal that the proposed approach achieves 2.71% higher recognition accuracy and faster detection speed compared to the original Faster RCNN. Crop disease detection is vital for maintaining crop quality and preventing diseases. Traditional manual observation methods are inefficient and unreliable due to limited expertise and availability of agricultural experts. The proposed method overcomes these challenges by leveraging the Faster RCNN algorithm to detect and recognize diseased tomato leaves while accurately localizing the affected areas.

3. METHODOLOGY

3.1 System Architecture

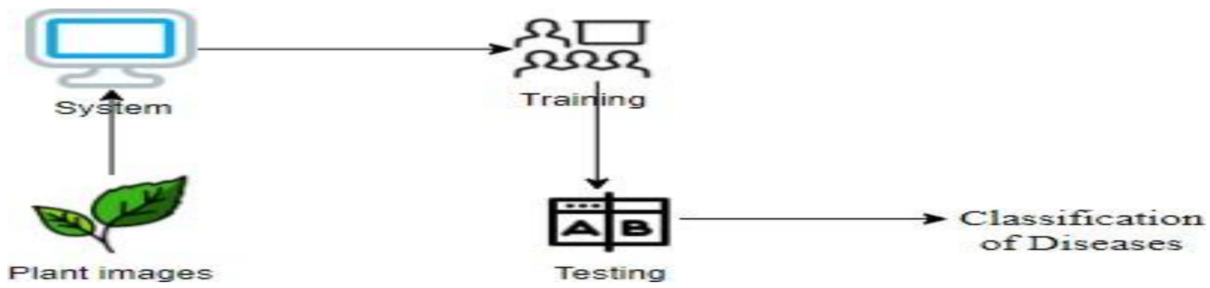


Fig.3.1 System Architecture

3.2 Procedure

1. ***Input Data*****:** The system takes input data in the form of images, text, audio, or other types of data, depending on the classification task.
2. ***Preprocessing****:* The input data may undergo preprocessing steps such as normalization, resizing, filtering, or feature extraction to enhance the data quality or extract relevant features for the classification task.
3. ***Neural Network Layers****:* The core of the system is composed of multiple layers of artificial neurons, organized in a hierarchical manner. These layers typically include:
   Input Layer: Receives the preprocessed data as input and passes it to the subsequent layers.
   Hidden Layers: Consist of one or more layers that perform complex transformations and learn hierarchical representations of the input data. These layers may include convolutional layers, recurrent layers, or fully connected layers, depending on the architecture.
   Output Layer: Produces the final output of the network, which represents the predicted class or classes for the input data. The activation function applied in the output layer depends on the classification problem, such as softmax for multi-class classification or sigmoid for binary classification.
4. ***Training Algorithm:*** Deep learning models are trained using optimization algorithms, such as stochastic gradient descent (SGD), Adam, or RMSprop. These algorithms iteratively adjust the weights and biases of the network based on the discrepancy between the predicted outputs and the true labels in the training data.
5. ***Loss Function:*** A loss function measures the discrepancy between the predicted outputs and the true labels during training. Common loss functions include categorical cross-entropy for multi-class classification and binary cross-entropy for binary classification.
6. ***Backpropagation****:* During training, the gradients of the loss function with respect to the network parameters are computed using backpropagation. These gradients are then used to update the weights and biases in the network, iteratively improving the model's performance.

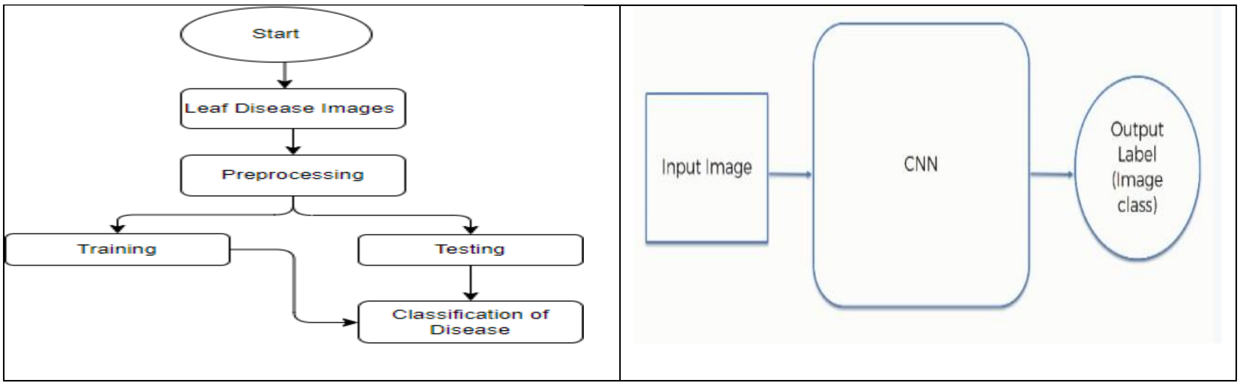
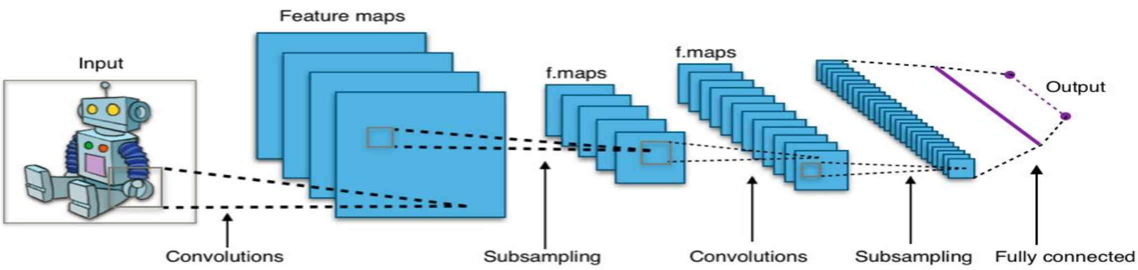


Fig.3.2 Process flow

3.3 Algorithm: Convolutional Neural Network

The Convolutional Neural Network (CNN) algorithm proceeds through the following steps:

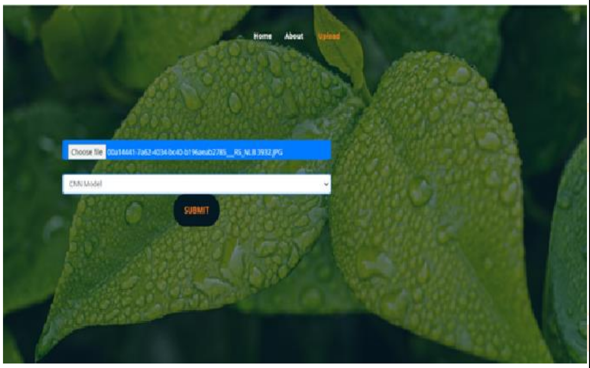
1. ***Input Image***: The algorithm takes an input image represented as a grid of pixels, each containing color or intensity information.
2. ***Convolution Operation****:* The input image is convolved with learnable filters or kernels. These filters slide over the image, performing element-wise multiplication and summation operations to extract relevant features.
3. Activation Function: An activation function, such as ReLU, is applied element-wise after the convolution operation. It introduces non-linearity to capture complex patterns and enhance feature representation.
4. *Pooling* ***Operation:*** The feature maps obtained from the previous layer undergo downsampling using techniques like max pooling or average pooling. This reduces spatial dimensions while preserving important information.
5. ***Fully Connected Layer:*** The pooled features are flattened into a 1D vector and connected to a fully connected layer. Similar to traditional neural networks, this layer learns higher-level features by connecting all neurons from the previous layer to the subsequent layer.
6. ***Output Layer:*** The final layer of the CNN produces classification or prediction results. The output layer may employ different activation functions depending on the task. For multi-class classification, softmax activation is commonly used to generate probability scores for each class.
7. ***Training:*** The CNN is trained by optimizing its parameters, such as weights and biases, using a labeled training dataset. A loss function is defined to measure the difference between predicted and true labels. Backpropagation and gradient descent techniques are employed to adjust the parameters and minimize the loss.
8. ***Prediction:*** Once trained, the CNN can make predictions on unseen images. The input image is passed through the trained network, and the output layer produces the predicted class label or probability distribution over classes.



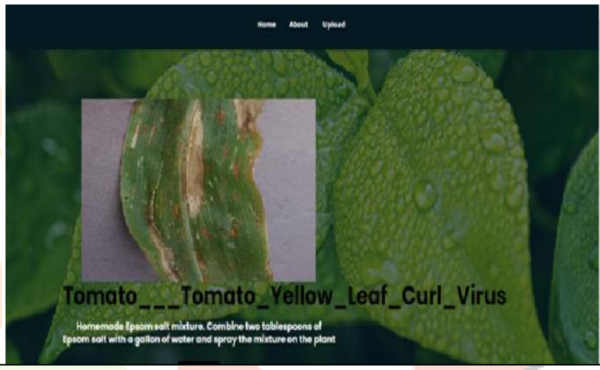
4. EXPERIMENTAL SNAPSHOTS

4.1 Sample Tomato Data set images

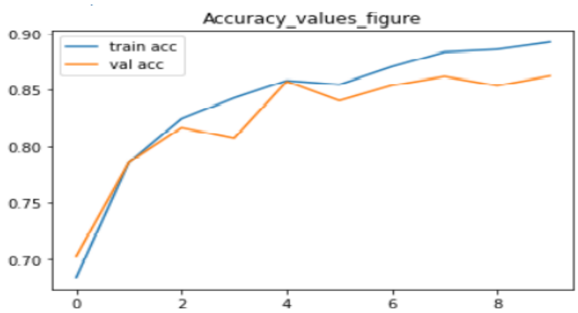
4.2 Test image upload



4.3 Classified Result



4.4 Analysis: Loss Score and Accuracy Score



In a total of 300 images, a comprehensive analysis detected 818 tomato leaves. Out of these leaves, 260 were identified as diseased while others were identified as healthy. However, during the identification process, some errors occurred among the 210 diseased leaves,. Surprisingly, only one leaf was incorrectly identified as healthy, while 16 diseased leaves were mistakenly identified as having other diseases. Furthermore, a small fraction of the diseased leaves, approximately 0.72%, were misidentified as healthy, while 5.42% of the diseased leaves were erroneously labeled as having different diseases.

5. CONCLUSION

Agriculture plays a crucial role in the economic development of a nation and is considered an integral part of society. This study focuses on the fundamental concept of detecting plant leaf diseases and understanding various symptoms associated with them. Initially, our research aimed to cover multiple crops and their respective diseases comprehensively. However, considering our limited knowledge and experience during this learning and practice phase, we realized it would be challenging to achieve that within the given timeframe. Therefore, we narrowed our focus to the staple crop of our own country, tomatoes. Further work can be shifted to identifying and understanding all the diseases and their causes that can be inferred from changes occurring in the leaves of tomato plants.

6. REFERENCES

1. 1.H. Lu, Y. Li, T. Uemura, H. Kim, and S. Serikawa,(2018) ‘‘Low illumination underwater light field images reconstruction using deep convolutional neural networks,’’ Future Gener. Comput. Syst., vol. 82, pp. 142–148.

2. Z. Chuanlei, Z. Shanwen, Y. Jucheng, S. Yancui, and C. Jia,(2017) ‘‘Apple leaf disease identification using genetic algorithm and correlation based feature selection method,’’ Int. J. Agricult. Biol. Eng., vol. 10, no. 2, pp. 74–83

3. I. Goodfellow, Y. Bengio, and A. Courville (2016). *Deep Learning*, MIT Press.

4. A. Gongal, S. Amatya, M. Karkee (2015). Q. Zhang, and K. Lewis, “Sensors and systems for fruit detection and localization: A review,” *Computers and Electronics in Agriculture*, vol.116, pp.8–19.

5. J. Garcia and A. Barbedo (2014). “Using digital image processing for counting whiteflies on soybean leaves,” *Journal of Asia-Pacific Entomology*, vol.17, pp.685–694.

6. S. Ji-Yong, Z. Xiao-Bo, Z. Jie-Wen, W. Kai-Liang, C. Zheng-Wei et al May (2012)., “Nondestructive diagnostic of nitrogen deficiency by cucumber leaf chlorophyll distribution map based on near infrared hyperspectral imaging,” Scientia Horticulturae, vol.138, pp.190–197.

7. J.S. Cope, D. Corney, J.Y. Clark, P. Remagnino, and P. Wilkin (2012). “Plant species identification using digital morphometrics: A review,” *Expert Systems withApplications*, vol.39, pp.7562–7573.

8. S. Ji-Yong, Z. Xiao-Bo, Z. Jie-Wen, W. Kai-Liang, C. Zheng-Weietal (2012). “Nondestructive diagnostic of nitrogen deficiency by cucumber leaf chlorophyll distribution map based on near infrared hyperspectral imaging,” *ScientiaHorticulturae*, vol.138, pp.190–197.
9. A. Krizhevsky, I. Sutskever, and G. E. Hinton (2012). “Imagenet classification with deep convolutional neural networks,” *Proceedings of 25th Advances in Neural Information Processing Systems*, pp. 1097–1105.

10. T. Rumpf, A.-K. Mahlein, U. Steiner, E.-C. Oerke, H.-W. Dehne, and L. Plümer, (2010) ‘‘Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance,’’ Comput. Electron. Agricult., vol. 74, no. 1, pp. 91–99.

11. L. Yuan, Y. Huang, R. W. Loraamm, C. Nie, J. Wang, and J. Zhang,(2004) ‘‘Spectral analysis of winter wheat leaves for detection and differentiation of diseases and insects,’’ Field Crops Res., vol. 156, no. 2, pp. 199–207.

12. Camargo and J.S. Smith (2009). “An image-processing based algorithm to automatically identify plant disease visual symptoms,” *Biosystems Engineering*, vol.102, pp.9–21.

13. J. Hemming and T. Rath (2001). "Computer-vision-based weed identification under field conditions using controlled lighting," *Journal of Agricultural Engineering Research*, vol.78, no.3, pp.233–243.