

A NOVEL IOT BASED PEST IDENTIFICATION AND CLASSIFICATION USING CNN AND LSTM

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ABSTRACT

Citrus crops are often damaged by pest infestation, which is a persistent problem for growers and often leads to significant declines in output and profitability. Traditional pest detection techniques rely on direct observation by field workers, which is labour-intensive, time consuming and sometimes unreliable. In order to detect and categorize citrus pests in real time, this study proposes an internet of things (IoT) based automated bug detection system that makes use of convolutional Neural Networks (CNN) and Long Short Term Memory (LSTM) networks. Images from IoT-enabled field cameras are processed using a lightweight hybrid deep learning techniques to extract features and make fast conclusions on devices with limited processing power. Six important citrus pest species are represented by the 1,200 images in this experimental dataset which was collected from a citrus research station in Tamil Nadu, India. With an accuracy of 95.4%, the evaluation results demonstrate that our hybrid CNN-LSTM architecture performs better than both traditional CNN and conventional machine learning models. By facilitating automated field monitoring early insect detection and timely decision making the proposal method reduces crop losses and the need for pesticides.

Keywords: *Artificial Intelligence (AI), Internet of Things (IoT), Citrus, CNN, LSTM, Pests*

1. INTRODUCTION

Citrus plants are an essential part of the world's agricultural output and have a big impact on both local and worldwide trade. Due to their nutritional, therapeutic, and commercial benefits, citrus crops—which are members of the Rutaceae family—are widely grown. The crop's business implication is added augmented by the handling of its crop, which embrace fresh fruits, juices, essential oils, and pectin, in a variety of industry, including food, pharmaceuticals, and cosmetics [1]. However, pests and diseases give a steady warning to citrus agricultural, unenthusiastically distressing fruit quality and output [2], [3]. Common pests are depict in Figure 2, while common citrus cultivars are shown in Figure 1.



Figure 1. Types of citrus fruits

Data Source: Compiled from agricultural records and open-access citrus databases; sample fruit images adapted from [2], [3].

Pest infestations prolong to have a major unenthusiastic collision on crop output and productivity. General citrus pests that cause important harm to fruit and leaves include aphids, mealybugs, citrus leafminers, and light brown apple moths [3]. These pests often prowl under the foliage

during the day, make early finding complex. By the occasion damage is perceptible infestations are usually extensive, require extra insect killer application [4]. Even after wash, insect killer residue can still be damaging to the surroundings and human being health.



Figure 2. Various types of citrus pests

Data Source: compile as of undeveloped records and open-access citrus databases sample fruit images modified from [2], [3].

Pest recognition is a tough task due to the complex morphology of insects and the similarity between kind [5], [6]. Identification methods that are traditional require much work and time and can be erroneous [7]. Insect damage constitute 17–23% of total agricultural losses globally, with yield reduction of up to 50% in confident areas [8]–[10]. Hence, efficient pest organization and prompt finding are very important for boost undeveloped efficiency and guarantee sustainable food systems. Diseases transmit by insects, counting canker, fruit scab, greening disease (Huanglongbing), and black spot, reduce both the yield and market quality of citrus fruits [11]. The primary citrus diseases and the species they impact are detailed in Table 1.

The options for precision agricultural methods have enlarged due to recent technological advancement. By facilitate computerization based on data and decisions made in real time, the Internet of Things (IoT) technology has distorted a number of sectors, including healthcare, communication, energy, and agriculture [12], [13]. In the agricultural sector, IoT sensors, drones, and wireless communication technology like LoRa are being utilized more and more for purposes such as field monitoring, pest management, and assembly environmental data [14], [15]. Farmers can reduce expenses, boost output, and achieve improved system addition via remote connectivity thanks to these technologies.

Agricultural monitor systems have been transformed by the alliance of deep learning (DL), Artificial Intelligence (AI), and Internet of Things (IoT) technology. CNNs in deep learning approach have yield significant results in picture

classification and disease discovery applications by detect spatial patterns in large image datasets. When it comes to differentiating between sick and healthy crops, these models are very precise. Despite these advancement, many systems still solely rely on CNNs and lack IoT-based real-time monitoring. This creates a gap in early identification and automated pest treatment in field settings.

Table 1 – Typical diseases of citrus plants

(Data Source: compile as of farming records and open-access citrus database; sample fruit images modified from [2], [3])

Citrus Species	Diseases
Orange (Citrus sinensis)	Frequently affected by citrus canker of bacterial origin, dark lesion formation on leaves and fruits, melanose infections, Penicillium-based rots, Phytophthora-related decay, scab formation, and various stem or end-rot conditions.
Lemon (Citrus limon)	Typically experiences anthracnose infection, aphid-associated damage, canker caused by bacteria, and the well-known citrus greening disorder.
Mandarin (Citrus reticulata)	Susceptible to Alternaria-related fruit rot, blue and green molds, gray mold infection, sour rot, and mucor-induced spoilage.
Grape fruit (Citrus paradise)	Common problems include anthracnose, black spot lesions, citrus blast, symptoms of citrus greening, scab infections, and melanose.

The current work proposes an Internet of Things-enabled pest detection and classification system that uses CNN and deep learning-based image analysis to identify and classify citrus pests in order to address this problem. A trained CNN model analyzes real-time images and environmental data collected by IoT devices from citrus orchards to determine the type and presence of insects. This advance boost discovery speed and accuracy, reduces manual involvement, and encourages timely pest management responses.

In end, the objective of this research is to create a web-based hybrid deep learning framework for the image-based detection of pests in citrus crops using CNN (Convolutional Neural Network) technology. This system aims to offer a farmer a method of pest monitoring that is automated, scalable, and efficient. This study advances

sustainable practices, bolsters precision agriculture, mitigate crop losses, and boosts citrus fruit yields through the smart detection and management of pests.

2. LITERATURE REVIEW

The literature has addressed a number of insect detection-related topics. Different datasets and pest identification algorithms are explored according to the detection of tiny pests and other pest species under various environmental circumstances. This section addresses current research in agriculture, encompassing different kinds of artificial intelligence technologies, Internet of Things sensors, and aerial drones.

2.1 Internet of Things

In 2021, Kumar et al. introduced a revolutionary method for detecting pests that reduce rice production [16]. Information was extracted from photographs of rice pests sent to the cloud using IoT technology. As soon as a pest was discovered, farmers and landowners were notified, allowing them to take precautionary measures. Analysis shows that this pest monitoring method has reduced rice losses in the producing area. Chen et al. [17] developed a DL-based model for collecting pest locations in 2020 using the latest advances in deep learning. Experimental results show that the proposed approach increases detection accuracy.

The authors of [18] proposed an IoT and drone-based early detection and response system for cotton plant pests. They developed a method for effectively classifying and identifying pests. Researchers in [19] suggested a method for identifying plant pests using IoT sensors. In order to increase the classification system's efficacy in finding pests in crops, they also used the Adaptive Honey Badger approach. The approach suggested by Zhibin.W et.al, [20]uses IoT technology to detect and control the pests in various crops.

2.2 Neural Networks in classification

Venkataramanan et al. [21] developed a DL algorithm to identify and classify plant diseases by examining the leaves of plants. Their research involves a multi-stage classification process that eliminates potential errors at each stage, resulting in improved accuracy in the predictions. Image

segmentation can be utilized to break down a large dataset, with the outcomes subsequently fed into AI based systems for disease detection [22]. In the context of image classification for rice leaf diseases, discriminative fine-tuning proves to be more effective than fine-tuning with a cyclical learning rate for CNN architectures [23] (Bhujel and Shakya).

Xinyu J. et al. [24] employed an Attentive Recurrent Generative Adversarial Network (AR-GAN)-based data augmentation approach to balance the dataset. They expanded each sort of citrus pest into roughly 1500 samples in order to solve the problem of uneven distribution among bug kinds. A method for identifying leafhoppers and whiteflies was proposed by Li et al. [25]. Data were gathered in a greenhouse setting, and sticky traps were used to take pictures. In contrast to Faster R-CNN, which performs poorly in identifying little pests and uses sticky trap photos, a two-stage bespoke detector was developed. This model performs worse when evaluated on images with complicated backgrounds.

Deep learning models were used by Rustia et al. [26] to automatically identify pests in traps. To identify and remove unnecessary items from the traps, a CNN model was used. The main goal of this study was to create a prototype for identifying and numbering the bugs in each photograph. Rahman et al. [27]created an alternative deep learning approach for identifying and recognizing diseases and pests in images of rice plants. They utilized and enhanced VGG16 and InceptionV3 for this purpose, and their findings were evaluated with the outcome of existing methods discussed earlier in the literature. In [28],Legaspi et al. employed Darknet Architecture with Yolov3 to identify whiteflies and fruit flies, but the model faced challenges in detecting small pests in complex environments, leading to low accuracy. Additionally, [29]applied YOLOv2 and YOLOv3 to identify pests and diseases in tea plantations, achieving accuracies of 58% and 60.8% for identifying small pests. There is a potential for using an improved DL algorithm for better recognition of small objects.

In [30]the authors have developed an affordable DL approach for automatically identifying and catagorizing the pests. They introduce Faster-Pest Net model, which utilizes the MobileNet framework as its primary network to gather detailed features. Setiawan et al.

[31] employed the IP102 dataset and trained a CNN system for pest detection. This study optimized tiny MobileNetV2 models using frozen layers, sparse regularization, and dynamic learning rate in combination with CutMix augmentation. Combining such methods throughout training allowed for the highest accuracy of 71.32%.

The anchor-free region convolutional neural network (AF-RCNN) method was used by Liu et al. [32] to identify agricultural pests across many categories. This technique produced 85.1% of recall and 56.4% of mean Average Precision (mAP) on a dataset containing 24 types of pests. Sabanci et al. [33] integrated several deep learning frameworks such as R-CNN, Faster R-CNN, SSD, VGG, and residual networks to detect nine different pest and disease types found in tomato plants. Similarly, Roy et al. [34] proposed a rapid, fine-grained detection technique using an enhanced version of the YOLOv4 model to achieve better accuracy.

3. PROPOSED APPROACH

This study proposes a novel pest detection framework that combines Internet of Things (IoT) technology with Deep Learning (DL) models to identify and classify citrus pests accurately. CNN and LSTM are combined in the hybrid model known as NICLNet (Novel IoT-based CNN with LSTM). This approach seeks to improve overall crop productivity and quality by detecting insect infestations early on and employing fewer fertilisers and pesticides.

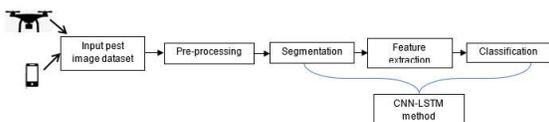


Figure 3. Processing Steps of the proposed system

The proposed system consists of three main modules:

- (i) Image acquisition module,
- (ii) Data processing module, and
- (iii) Image classification module.

The complete workflow, showing the sequential stages from data collection to model-based classification, is illustrated in Figure 3.

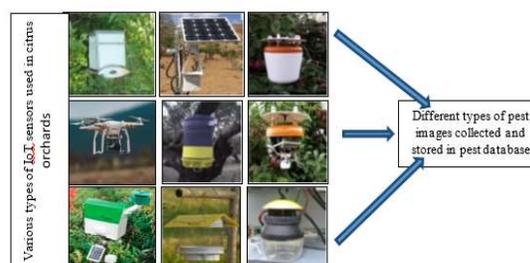
3.1 Image capturing module

This system uses a network of IoT-enabled sensors and cameras installed in citrus plantations to continuously monitor and collect images of pests at various stages of crop growth. Precision agriculture, smart cities, and healthcare are just a few of the sectors where IoT-based remote monitoring is increasingly essential [35]. This paper claims that IoT enables real-time monitoring and management of insect activity in citrus plantations from any location.

As shown in Figure 4, a range of IoT-based imaging devices, including optical traps, bucket traps, and camera sensors, were used to collect two primary forms of data.

- Image data: IoT cameras and traps have taken high-resolution photos of citrus pests.
- Time-series data: Temporal data that shows patterns of pest recurrence over time, which aids in identifying seasonal trends and infestation frequency.

We used widely available image-based bug detectors made by companies such as EFOS (Environmental and Food Safety Solutions and Services). These sensor-equipped traps can efficiently detect large moth species, such as *Helicoverpa armigera*, *Autographa gamma*, and *Spodoptera* species. The large-scale orchard monitoring was supported by Unmanned Aerial Vehicles (UAVs) or drones equipped with high-resolution cameras to capture aerial images from



multiple viewpoints.

This combination of ground-level IoT

Figure 4. Different types of IoT based pest sensors

sensors and aerial drone imagery provides comprehensive coverage and enhances the accuracy of pest monitoring across extensive citrus plantations. All captured images are securely transmitted via wireless networks to the central server for further analysis and stored in the pest image database.

It can remotely identify the insects such as *Helicoverpa armigera*, *Autographa gamma* and *Spodoptera* spp. The large area of the citrus

orchard is monitored by the Unmanned Aerial Vehicle (UAV) or drones fixed with camera.

3.2 Data processing module

The collected pest images undergo a series of pre-processing operations designed to improve image quality and enhance model accuracy. These steps include trimming, rotation, noise addition, contrast adjustment, edge sharpening, and grayscale transformation. Such pre-processing ensures that images maintain consistent format and clarity before being used for training the model.

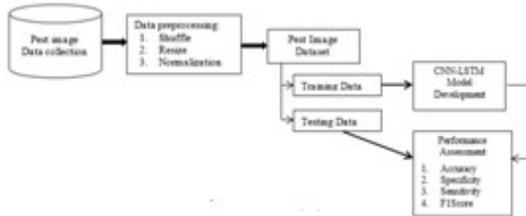


Figure 5. Architecture of the proposed system

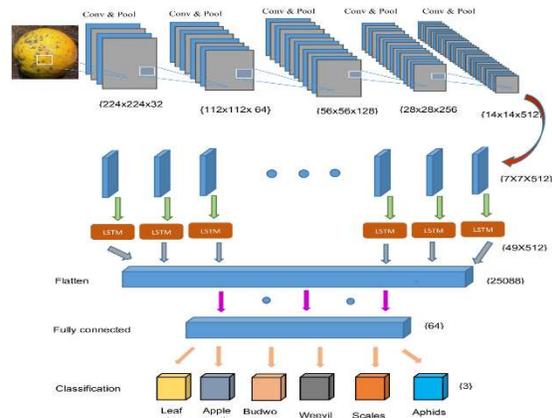
Each image was resized to 256×256 pixels with a resolution of 72 dpi, shuffled to prevent bias, and adjusted so that pixel intensities fall within the 0–1 range. This normalization improves model convergence during training. The final dataset was partitioned into three groups: 70% for training, 15% for validation, and 15% for testing. The training portion supported parameter learning, whereas the validation and test portions were used to assess how well the model generalized to unseen data. Data augmentation was applied to increase the variety of training samples and avoid overfitting. The techniques included random flipping, rotation ($\pm 30^\circ$), cropping, Gaussian noise, and brightness modification. The overall architecture and data flow of the system are shown in figure 5.

3.3 Image Classification phase

The classification module is based on a hybrid CNN–LSTM deep learning model, which combines the strengths of spatial and temporal feature learning. In order to enhance classification performance, the CNN extracts crucial spatial features from the insect images, and the LSTM records the sequential dependencies between these feature maps.

3.3.1 CNN Architecture

CNNs represent one of the most effective deep learning models for tasks such as image classification and object detection [36–40]. A typical CNN includes an input layer, multiple intermediate layers, and an output layer. The intermediate layers generally carry out convolution operations, pooling, and fully connected



processing.

Figure 6. CNN-LSTM – network architecture

The mathematical expression for the convolution operation is as follows: F is the final feature map, K is the 2D filter, and I is the input image matrix.

$$F(i, j) = (I * K)(i, j) = \sum \sum (i+m, j+n)K(m, n) \quad (1)$$

Non-linearity is introduced using the Rectified Linear Unit (ReLU) activation function after the convolution layer:

$$f(x) = \max(0, x) \quad (2)$$

To lower computing complexity and guarantee translation invariance, pooling layers (PL) down sample the feature maps. To keep the most important characteristics, max pooling is typically utilized. Lastly, the high-level collected features are interpreted for classification by one or more fully connected (FC) layers.

3.3.2 LSTM Architecture

The Long Short-Term Memory (LSTM) network is one type of recurrent neural network (RNN) that effectively handles sequence modelling issues and long-term dependencies [43]. LSTM introduces input, forget, and output gates to control information flow and mitigate the vanishing gradient problem.

The gating mechanisms are defined as follows:

$$I_t = \sigma(W_i[h_{t-1}, X_t] + b_i) \quad (3)$$

$$\tilde{C}_t = \tanh(W_i[h_{t-1}, X_t] + b_i) \quad (4)$$

$$C_t = f_i C_{t-1} + i_t \tilde{C}_t \quad (5)$$

where

W_i represents the weight matrices;

b_i represents bias of the input gate;

C_t denotes the memory function;

\tilde{C}_t – tanh output

$$f_i = \sigma(W_f[h_{t-1}, X_t] + b_f) \quad (6)$$

In this equation,

W_f represent the weight matrix;

b_f represents the offset value and

σ denotes the sigmoid function

in conclusion, the output entry compute the new concealed condition:

$$O_t = \sigma(W_o[h_{t-1}, X_t] + b_o) \quad (7)$$

$$h_t = O_t \tanh(C_t) \quad (8)$$

Where W_o denote the power matrix of the output entry

The suggested model makes use of CNN's spatial feature extraction capabilities and LSTM's capacity to represent temporal dependencies. When compared to solo CNN or conventional machine learning models, this hybrid architecture achieves better classification accuracy in insect identification. Figure 6 depict the last design, which consists of a fully linked categorization cover after a series of convolution, pooling, and recurrent layers.

3.4 Experimental Setup

The experiment for this study were carried out on a workplace with an Intel® Core™ i7-10700 CPU (2.90 GHz), 32 GB of RAM, and an Nvidia GeForce RTX 2070 GPU to facilitate rapid deep learning calculations. This process utilized the TensorFlow-GPU 2.6.0, Keras 2.6, and Python 3.8 libraries. Thanks to this configuration, the training and evaluation of the proposed CNN-LSTM model were successful.

3.5 Summary of the Proposed Framework

The suggested NICLNet system combine IoT sensing, data pre-processing, and hybrid deep learning to make possible clever pest identification in citrus crops. This method reduces the need for human involvement, allows for real-time examination of pests, and offers move on alerts for preventive action. The experimental findings presented in Section 4 show that the suggested CNN-LSTM architecture provides greater accuracy, precision, and reliability than traditional methods, underscore its relevance for intelligent and sustainable agriculture.

4. EXPERIMENTS AND RESULTS

The investigational answers of the anticipated NICLNet approach are obtainable in this section with the assessment of its show using average arrangement metrics. Training and validation behavior was monitored using loss and accuracy curves to assess the stability and generalization capability of the model. All experiments were conducted on the dataset described in section 4.1.

To measure the effectiveness of the proposed approach, four quantitative evaluation metrics are employed: accuracy (Ac), precision (Pr), recall (Rc), and specificity (Sp). The evaluation metrics were computed using the conventional mathematical expressions defined for each measure:

$$Ac = (TP+TN) / (TP+TN+FP+FN) \quad (9)$$

$$Pr = TP/(TP+FP) \quad (10)$$

$$Rc = TP/(TP+FN) \quad (11)$$

$$Sp = TN/(TN+FP) \quad (12)$$

These indicators help to determine how effectively the model identifies and classifies citrus pests across different categories.

4.1 Dataset description

Insect images obtained from "https://github.com/xpwu95/IP102" are needed for the proposed IoT pest detection model. This dataset contains almost 75,000 pictures in 102 different categories. The dataset is split into three subsets as 70% of samples for coaching the proposed model, 15% of samples for validation and the remaining 15% dataset for testing. In this research, the iteration, batch size, and learning rate of the model's hyper-parameters are set to develop

the ultimate optimized model. The study employed the Stochastic Gradient Descent (SGD) training optimizer with learning rates set at 0.0015. The epoch was set at 200 and the batch size at 32.

4.2 Training and Validation Performance

The training performance of NICLNet was compared with existing baseline models. The precision, recall, and F1-score attained during training are compiled in Table 2.

The training performance of NICLNet in comparison to deep learning and conventional machine learning models is displayed in Table 2. The results show that NICLNet improves stability and accuracy across all evaluation metrics.

Table 2. Training performance of baseline models and NICLNet

(Data Source: Experimental results generated by authors)

The Model's Name	Accuracy of Training	Accuracy of Validation	Training Time (ms)
CNN-SVM [44]	84.22	85.45	155
CNN-KNN	92.22	87.88	198
CNN-RF	79.00	83.15	146
GoogleNet [45]	86.25	83.25	148
VGG-19 [46]	87.56	91.13	136
Niclnet	96.44	93.52	138

4.3 Performance Comparison with Existing Approaches

Table 3 presents a thorough comparison between NICLNet and current state-of-the-art techniques. This table shows how well NICLNet classifies photos of citrus crop pests in a number of different ways. Table 3 demonstrates that NICLNet outperformed all assessed benchmark models with 96.44% accuracy, 95.40% precision, 93.45% recall, 93.25% specificity, and a 92.22% F1-score.

Table 3. Performance comparison of NICLNet with existing approaches

(Data Source: Experimental results generated by authors)

Techniques	Accuracy	Precision	Recall	Specificity	F1-Score
CNN-SVM	84.22	82.43	81.22	81.16	80.23
CNN-KNN	92.22	91.00	90.42	90.25	89.23
CNN-RF	79.00	78.98	76.20	76.23	75.23
GoogleNet	86.25	85.10	83.40	81.78	80.65
VGG-1	87.56	87.44	86.35	85.90	85.10
Niclnet	96.44	95.40	93.45	93.25	92.22

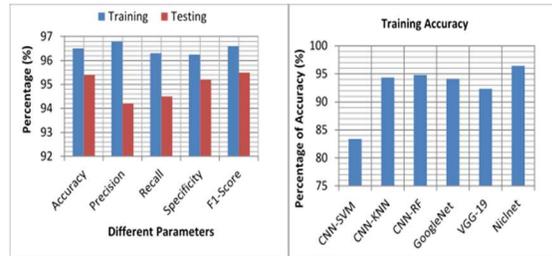


Figure 8. Training and testing performance of Niclnet for different hyper parameters



Figure 9. Comparative analysis of training performance of Niclnet and other existing methods

The experiment results are shown in Figures 7 through 11. The training and testing trends of NICLNet are shown in Figure 7. Figure 8 compares NICLNet's training performance with previous models. Figure 9 compares the testing performance with existing methods. The variation in learning rates is shown in Figure 10.

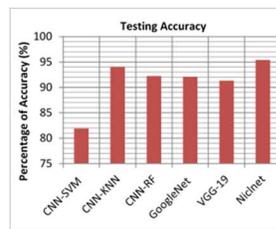


Figure 10. Comparative analysis of testing performance of Niclnet and other existing methods

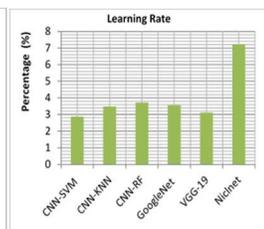


Figure 11. Comparative analysis of learning rate of Niclnet and other existing methods

Figure 11 provides a graphical comparison of performance metrics, clearly showing that NICLNet maintains superior accuracy and recall across all classes

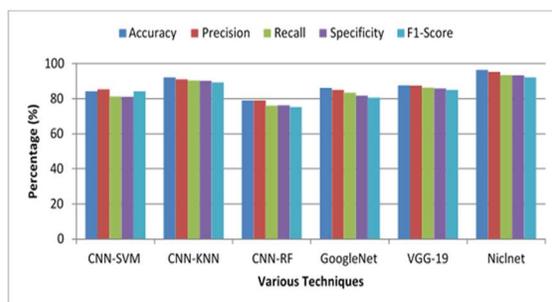


Figure 11. Comparative analysis of N1CLNet and other existing methods for various hyper-parameters

(Data Source: Experimental results generated by authors)

5. CONCLUSION

The goal of this study is to explore how deep neural networks and Internet of Things technologies might be combined to enhance pest management strategies for citrus crops. The recommended incorporation exemplify the wider advantages of inclusion unbroken environmental monitoring with cognitive analytics, which facilitates decision-making that is both timely and well-informed. The argument highlights the potential of such a system to modernize pest management into a proactive, data-driven approach that improves receptiveness and promotes environmental responsibility, rather than focussed on particular detection outcomes. The whole framework emphasize a general stage that can be tailored to various crops and agricultural contexts, while also stress the implication of real-time monitoring, adaptive learning, and under fire interference.

To conclude, there is guarantee in combine IoT and DNN technologies for developing agricultural solutions that are both scalable and sustainable. This approach will gain greater significance in modern precision agriculture and long-term ecosystem management as future studies apply these concepts to a wider range of systems and autonomous field operations.

REFERENCES:

- [1] Iqbal Z, Khan MA, Sharif M, Shah JH, urRehman MH, Javed K. 2018. An automated detection and classification of citrus plant diseases using image processing techniques: A review. *Comput Elect Agric* 153: 12 - 32. <https://doi.org/10.1016/j.compag.2018.07.032>.
- [2] <https://pestsofbhutan.nppc.gov.bt/wp-content/uploads/2017/07/Main-content.pdf>
- [3] <https://www.agric.wa.gov.au>
- [4] Xing S, Lee M, Lee K-k (2019) Citrus pests and diseases recognition model using weakly dense connected convolution network. *Sensors* 19(14):3195
- [5] Sourav Kumar Bhoi, Kalyan Kumar Jena, Sanjaya Kumar Panda, Hoang Viet Long, Raghvendra Kumar, P. Subbulakshmi, Haifa Bin Jebreen, An internet of things assisted unmanned aerial vehicle based artificial intelligence model for rice pest detection, *Microprocess. Microsyst.* 80 (2021) 103607.
- [6] C.J. Chen, Y.Y. Huang, Y.S. Li, C.-Y. Chang, Y.-M. Huang, AnaIoT based smart agricultural system for pests detection, *IEEE Access* 8 (2020) 180750–180761.
- [7] TurkogluMuammer, Berrinyanikoğlu and davuthanbay, PlantDiseaseNet: convolutional neural network ensemble for plant disease and pest detection, signal, image and video processing, 2021.
- [8] Donatelli, M.; Magarey, R.D.; Bregaglio, S.; Willocquet, L.; Whish, J.P.; Savary, S. Modelling the impacts of pests and diseases on agricultural systems. *Agric. Syst.* 2017, 155, 213–224. [CrossRef] [PubMed]
- [9] Fried, G.; Chauvel, B.; Reynaud, P.; Sache, I. Decreases in crop production by non-native weeds, pests, and pathogens. In *Impact of Biological Invasions on Ecosystem Services*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 83–101.
- [10] Savary, S.; Willocquet, L.; Pethybridge, S.J.; Esker, P.; McRoberts, N.; Nelson, A. The global burden of pathogens and pests on major food crops. *Nat. Ecol. Evol.* 2019, 3, 430–439. [CrossRef] [PubMed]
- [11] Al-Hiary H, Bani-Ahmad S, Reyalat M, Braik M, Alrahamneh Z. 2011. Fast and accurate detection and classification of plant diseases. *Int J Comp Appl* 17: 31 - 38. <https://doi.org/10.5120/2183-2754>
- [12] Lin, J.; Yu, W.; Zhang, N.; Yang, X.; Zhang, H.; Zhao, W. A Survey on Internet of Things: Architecture, Enabling Technologies, Security and Privacy, and Applications. *IEEE Internet Things J.* 2017, 4, 1125–1142. [CrossRef]
- [13] Sisinni, E.; Saifullah, A.; Han, S.; Jennehag, U.; Gidlund, M. Industrial Internet of Things: Challenges, Opportunities, and Directions. *IEEE Trans. Ind. Inform.* 2018, 14, 4724–4734. [CrossRef]

- [14] Fangyuan Wang, Rujing Wang, Chengjun Xie, Jie Zhang, Rui Li, Liu Liu, Convolutional neural network-based automatic pest monitoring system using hand-held mobile image analysis towards non-site-specific wild environment, *Comput. Electron. Agric.* 187 (2021) 106268.
- [15] Husain, A. Jahir, and MA Maluk Mohamed. "IMBF-Counteracting Denial-of-Sleep Attacks in 6LowPAN Based Internet of Things." *J. Inf. Sci. Eng.* 35, no. 2 (2019): 361-374.
- [16] Sourav Kumar Bhoi, Kalyan Kumar Jena, Sanjaya Kumar Panda, Hoang Viet Long, Raghvendra Kumar, P. Subbulakshmi, Haifa Bin Jebreen, An internet of things assisted unmanned aerial vehicle based artificial intelligence model for rice pest detection, *Microprocess. Microsyst.* 80 (2021) 103607.
- [17] C.J. Chen, Y.Y. Huang, Y.S. Li, C.-Y. Chang, Y.-M. Huang, AnaIoT based smart agricultural system for pests detection, *IEEE Access* 8 (2020) 180750–180761.
- [18] Azfar, Saeed, Adnan Nadeem, Kamran Ahsan, Amir Mehmood, Hani Almoamari, and Saad Said Alqahtany. "IoT-based cotton plant pest detection and smart-response system." *Applied Sciences* 13, no. 3 (2023): 1851.
- [19] Kathole, Atul B., Jayashree Katti, Savita Lonare, and Gulbakshee Dharmale. "Identify and classify pests in the agricultural sector using metaheuristics deep learning approach." *Franklin Open* 3 (2023): 100024.
- [20] Wang, Zhibin, Xiaojun Qiao, Ying Wang, Hao Yu, and Cuixia Mu. "IoT-based system of prevention and control for crop diseases and insect pests." *Frontiers in Plant Science* 15 (2024): 1323074.
- [21] Venkataramanan A, Honakeri DKP, Agarwal P (2019) Plant disease detection and classification using deep neural networks. *Int J ComputSciEng* 11(9):40–46
- [22] Sungeetha A (2022) State of art survey on plant leaf disease detection. *J Innov Image Process* 4(2):93–102
- [23] Bhujel S, Shakya S (2022) Rice leaf diseases classification using discriminative fine tuning and CLR on EfficientNet. *J Soft ComputParadig* 4(3):172–187
- [24] Jia, Xinyu, Xueqin Jiang, Zhiyong Li, Jiong Mu, Yuchao Wang, and Yupeng Niu. "Application of deep learning in image recognition of citrus pests." *Agriculture* 13, no. 5 (2023): 1023.
- [25] Li, W.; Wang, D.; Li, M.; Gao, Y.; Wu, J.; Yang, X. Field detection of tiny pests from sticky trap images using deep learning in agricultural greenhouse. *Comput. Electron. Agric.* 2021, 183, 106048. [CrossRef]
- [26] Rustia, D.J.A.; Chao, J.J.; Chiu, L.Y.; Wu, Y.F.; Chung, J.Y.; Hsu, J.C.; Lin, T.T. Automatic greenhouse insect pest detection and recognition based on a cascaded deep learning classification method. *J. Appl. Entomol.* 2021, 145, 206–222. [CrossRef]
- [27] Rahman, C.R.; Arko, P.S.; Ali, M.E.; Khan, M.A.I.; Apon, S.H.; Nowrin, F.; Wasif, A. Identification and recognition of rice diseases and pests using convolutional neural networks. *Biosyst. Eng.* 2020, 194, 112–120. [CrossRef]
- [28] Legaspi, K.R.B.; Sison, N.W.S.; Villaverde, J.F. Detection and Classification of Whiteflies and Fruit Flies Using YOLO. In *Proceedings of the 2021 IEEE 13th International Conference on Computer and Automation Engineering (ICCAE)*, Melbourne, Australia, 20–22 March 2021; pp. 1–4.
- [29] Bhatt, P.V.; Sarangi, S.; Pappula, S. Detection of diseases and pests on images captured in uncontrolled conditions from tea plantations. In *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IV*; SPIE: Bellingham, WA, USA, 2019; Volume 11008, pp. 73–82.
- [30] Ali, Farooq, Huma Qayyum, and Muhammad Javed Iqbal. "Faster-PestNet: A Lightweight deep learning framework for crop pest detection and classification." *IEEE Access* (2023).
- [31] A. Setiawan, N. Yudistira, and R. C. Wihandika, "Large scale pest classification using efficient convolutional neural network with augmentation and regularizers," *Comput. Electron. Agric.*, vol. 200, Sep. 2022, Art. no. 107204.
- [32] W. Liu, G. Wu, F. Ren, and X. Kang, "DFF-ResNet: An insect pest recognition model based on residual networks," *Big Data Mining Anal.*, vol. 3, no. 4, pp. 300–310, Dec. 2020.
- [33] K. Sabanci, M. F. Aslan, E. Ropelewska, M. F. Unlarsen, and A. Durdu, "A novel convolutional-recurrent hybrid network for sunn pest-damaged wheat grain detection," *Food Anal. Methods*, vol. 15, no. 6, pp. 1748–1760, Jun. 2022.
- [34] A. M. Roy, R. Bose, and J. Bhaduri, "A fast accurate fine-grain object detection model based on YOLOv4 deep neural network,"

- Neural Comput.Appl., vol. 34, pp. 3895–3921, Jan. 2022.
- [35] Dan JericArcegaRustia, Jun-Jee Chao, Jui-Yung Chung and Ta-Te Lin, "An Online Unsupervised Deep Learning Approach for an Automated Pest Insect Monitoring System,"ASABE Annual International Meeting, January 2019.
- [36] Alzubaidi, L., Zhang, J., Humaidi, A.J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M.A., Al-Amidie, M. and Farhan, L., "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions." *Journal of big Data* 8, no. 1 (2021): 1-74. <https://journalofbigdata.springeropen.com/articles/10.1186/s40537-021-00444-8>
- [37] Krizhevsky, A., Sutskever, I., & Hinton, G. E., "ImageNet classification with deep convolutional neural networks." *Communications of the ACM* 60, no. 6 (2017): 84-90, <https://doi.org/10.1145/3065386>.
- [38]Hossain, MdAnwar, and MdShahriarAlamSajib. "Classification of image using convolutional neural network (CNN)." *Global Journal of Computer Science and Technology* (2019), <https://doi.org/10.34257/GJCSTDVOL19IS2PG13>.
- [39] A. Qayyum, C. K. Ang, S. Sridevi, M. K. A. A. Khan, L. W. Hong, M. Mazher, T. D. Chung, "Hybrid 3D-ResNet Deep Learning Model for Automatic Segmentation of Thoracic Organs at Risk in CT Images," 2020 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), pp. 1-5, 2020, <https://doi.org/10.1109/ICIEAM48468.2020.9111950>.
- [40] Phan, T.H., Tran, D.C. and Hassan, M.F., "Vietnamese character recognition based on CNN model with reduced character classes." *Bulletin of Electrical Engineering and Informatics* 10, no. 2 (2021): 962-969, <https://doi.org/10.11591/EEL.V10I2.2810>.
- [41] Mou, L. and Jin, Z., "Tree-Based Convolutional Neural Networks": Principles and Applications. Springer,2018. <https://vdoc.pub/documents/tree-based-convolutional-neural-networks-principles-and-applications-4cfkkikos1c0>
- [42] Zhou, Yu, Haipeng Wang, Feng Xu, and Ya-QiuJin. "Polarimetric SAR image classification using deep convolutional neural networks." *IEEE Geoscience and Remote Sensing Letters* 13, no. 12 (2016): 1935-1939. <http://dx.doi.org/10.1109/LGRS.2016.2618840>.
- [43] Kumar J, Goomer R, Singh AK. Long Short Term Memory Recurrent Neural Network (LSTM-RNN) Based Workload Forecasting Model For Cloud Datacenters. *Procedia Computer Science*. 2018; 125:676–682. Available from: <https://dx.doi.org/10.1016/j.procs.2017.12.087>.
- [44] Ü. Atila, M. Uçar, K. Akyol, and E. J. Uçar, "Plant leaf disease classification using EfficientNet deep learning model," *Ecol. Inform.*, vol. 61, Mar. 2021, Art. no. 101182.
- [45] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, "Microsoft COCO: Common objects in context," in *Computer Vision—ECCV*. Zurich, Switzerland: Springer, 2014, pp. 740–755.
- [46] Simonyan, K.; Zisserman, A. Very Deep Convolutional Networks for Large-Scale Image Recognition. *arXiv2014*, arXiv:1409.1556.