Review Article

Machine Learning for Detection of Pests in Tomato: A Review

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Abstract

Influence of a single atmospheric component or meteorological variable on the host, pathogen, or their interaction in controlled environments has accounted for the majority of climate change's impact on plant pests and diseases. Climate change can lead to alterations in the stages and rates of growth of pests and diseases, host resistance, and the physiology of host-pathogen or host-pest interactions, which can cause substantial harm and reduce tomato crop yields. Different approaches have been ineffective in the accuracy of pest and disease forewarning in past years. The remarkable progress in Deep Convolutional Neural Networks (DCNNs) is revolutionizing the early detection of pests and diseases in crops. By analysing vast amounts of present and historical climate data, alongside their expertise in object identification and image categorization, these AI models can predict outbreaks with impressive accuracy. However, understanding the specific microclimate suitable for each pest and disease is crucial for truly effective intervention. Combining these two elements creates a powerful, targeted approach to preserving crops. A forewarning system can help to reduce the use of pesticides, thereby reducing the cost of production and environmental pollution. Proper cloud servers and IoT-based sensor networks should be used for a better forewarning of pests and diseases in future circumstances.

Keywords: CNN, Machine learning, Microclimate, Pest forewarning, Tomato

Introduction

Climate change has been shown to have a substantial influence on the behaviour of pests and diseases in agricultural systems (Bebber *et al.*, 2013). Alterations in temperature and precipitation patterns substantially affect the behaviour of pests and disease vectors, creating unexpected challenges for farmers and agricultural productivity (Heeb *et al.*, 2019). Climate change may also have an impact on pest and disease vector life cycles and behaviour. Warmer winters might lower insect death rates, enabling their populations to increase more quickly in subsequent seasons. Similarly, changed precipitation patterns may generate circumstances that promote the reproduction and spread of disease-carrying organisms (Trebicki & Finlay, 2019). Besides, invasive species pose one of the biggest dangers to society, the economy, and global biodiversity (Early *et al.*, 2016; Sarukhán *et al.*, 2005). The inadvertent long-distance spread of invasive pests and diseases into areas outside of their natural distribution ranges has been greatly stimulated by climate change (Battisti & Larsson, 2015; Musolin, 2007). The establishment rate of invasive species has roughly quadrupled in the last 30-40 years in the European continent alone (Roques *et al.*, 2016) and the number of invasive forest diseases has escalated dramatically over the last 200 years (Santini *et al.*, 2013). Worldwide, it is acknowledged that the primary means of introducing invasive pests and diseases into the agricultural ecosystem is through the trade of planting materials (Brasier, 2008; Kenis *et al.*, 2007; Liebhold *et al.*, 2012; Santini *et al.*, 2013; Santini *et al.*, 2018). However, the equation is further complicated by the factor of climate change, which can act as a catalyst, altering the delicate interaction between hosts and pests within crop systems.

Pest forecasting is an important part of pest management. Pest forecasting refers to accurately predicting pest outbreaks using relevant data, a process vital for protecting the agri-food supply chain and the environment (Li *et al*., 2022). With proper forecasting, farmers can prepare and manage impending pest outbreaks, minimize unnecessary pesticide use, and reduce environmental pressures (Isard *et al*., 2015; Machekano *et al*., 2019). Within the realm of integrated pest management, a multifaceted approach is crucial for effective pest control. Machine learning has revolutionized the way pest and disease forecasting in agriculture has leveraged large datasets to develop predictive models (Ahmed, 2018). By analysing vast amounts of data, machine learning algorithms can identify patterns and make predictions with a high degree of accuracy (Pak & Kim, 2017). While machine learning (ML) offers powerful tools for rapid and accurate pest identification, understanding both weather and climate suitability is equally important for developing comprehensive control strategies. Integrating ML-based identification with weather and climate suitability modeling creates a robust and targeted approach to pest management, fostering sustainable agricultural practices.

Tomato is the most significant vegetable crop in the world economy and its output has grown significantly over time (Hu *et al*., 2023). *Lycopersicon esculentum* thrives in a warm, sun-drenched environment with well-drained soil. The optimal temperature range for tomato growth lies between 20 °C and 31 °C, with nighttime temperatures of 13 °C to 18 °C contributing to enhanced flavour and colour development. Moderate rainfall is sufficient for tomato cultivation, while excessive humidity can foster the proliferation of fungal diseases (Yang *et al*., 2019). Generally, tomatoes will be affected by high temperature and water stress (Hernandez-Espinoza & Barrios-Masias, 2020). Thus, an optimum microclimate is essential for effective fruit production and crop output. In addition to these, tomato plants are vulnerable to over 200 pests and diseases caused by pathogenic fungi, bacteria, viruses, and nematodes. Every pest and disease require a unique microclimate condition for their growth and development. Warm, humid circumstances often favour fungal diseases such as late blight in tomatoes, while cool nights and high humidity encourage the growth of Septoria leaf spots (Singh *et al*., 2018). Integrated pest management (IPM) requires a robust pest and disease surveillance system to deploy timely plant protection measures when needed to lower cultivation costs and prevent ecosystem contamination.

Recent integrated pest management studies indicate that weather variations significantly influence pest and disease outbreaks (Dhawan, 2016; Fuentes *et al*., 2017; Saeed *et al*., 2018). An essential component of pest control is recognizing the tomato crop's pest complex and its correlation with meteorological variables (Rawat, Karnatak, & Srivastava, 2020). When the ideal meteorological condition for a pest invasion is understood, it can facilitate pest detection (Alam *et al*., 2016). For efficient management of pests and diseases in modern agriculture, microclimate-based forewarning systems are essential. Tomato crop productivity and quality may be greatly increased with early detection and intervention, all while using fewer pesticides. Thus, understanding the relationship between host and pest, along with predicted weather patterns, allows for the prevention of pest and disease outbreaks (Balikai *et al*., 2021).

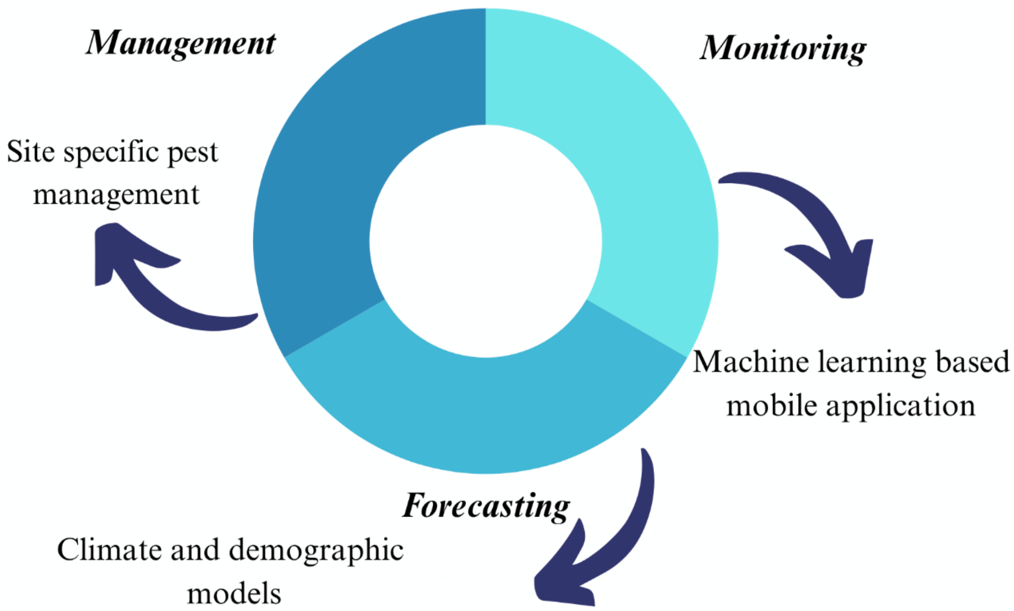

Fig. 1. Conceptualized framework for pest prediction and identification

Thus, the current article explores the past literature investigating machine learning applications in pest management and suitable microclimates for different pests and diseases affecting tomatoes.

Methodology

The search utilized databases including Google Scholar and Scopus. The search string used to collect information was outlined below:

(“Pest forewarning AND Tomato”, “Regression models” AND “Pest forewarning”, “Logistic models” AND “Pest forewarning”, “ARIMA model” AND “Pest forewarning”, “Machine learning” AND “Pest forewarning” AND “Tomato”, “Pests” AND “Tomato AND “Deep learning”, “Diseases” AND “Tomato” AND “Deep learning”)

To be included in the current review, articles needed to provide quantitative results about at least one aspect of pest forewarning models, neural network or influence of pest and diseases of Tomato based on micro climate.

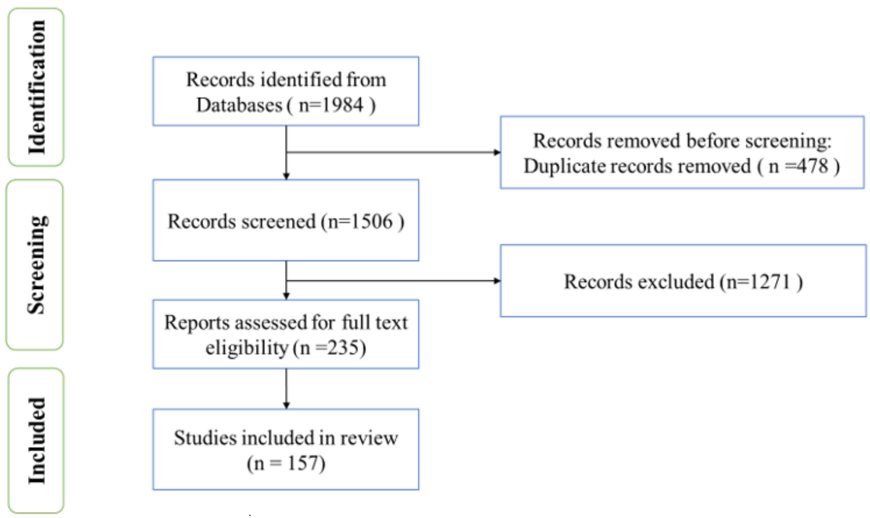

Fig. 2. Identification of studies via databases

Pest forewarning/detection

Advances in image processing and intelligent monitoring technologies have emerged as promising tools for early pest detection, enabling timely intervention and reducing the need for excessive pesticide application (Nagar & Sharma, 2020). These techniques leverage computer vision and machine learning algorithms to automatically identify pests, reducing the reliance on human experts and streamlining the pest management process (Ngugi *et al.*, 2021). By providing farmers with accurate and real-time information about pest infestations, these technologies can help them make informed decisions, leading to more sustainable and eco-friendly agricultural practices. Moreover, the integration of these systems with the Internet of Things (IoT) and decision support systems can further enhance the effectiveness of pest management, enabling coordinated efforts across larger geographic regions (Lima *et al.*, 2020).

Logistic and regression models

Previously, ordinal logistic models were used to forecast the pest/disease's occurrence. In cases where the data was quantitative, it was converted into dichotomous using threshold values. The model had the following form:

$$P\ (Y\ =\ 1) = = \frac{1}{1} + \exp\ (-L) \quad \text{and} \quad L\ =\ \sum \beta_i\, X_i \tag{1}$$

where X_i denotes the weather variables/weather indices. P< 0.5 indicates a low likelihood of an epidemic occurring, whereas P> 0.5 suggests a higher likelihood. The function L was constructed using several combinations of weather variables, including maximum and minimum temperatures, relative humidity (morning and evening), and mean relative humidity, as well as interactions. The combination that most accurately predicted the observed data was identified (Srivastava *et al.*, 2015). Later, stepwise regression models were used to forecast various aspects of rice, mustard, pigeon pea, sugarcane, groundnut, and cotton pests and diseases at various locations, including maximum pest population/disease severity, time of first appearance, time of maximum pest population/disease severity, and weekly pest population/disease severity. In this sort of model, two indices have been generated for each weather variable, one as a total of weather variable values in different weeks and the other as a weighted total, with weights representing correlation coefficients between the variable to forecast and the weather variable in those weeks. The first index represents the total amount of weather variable over the period under examination, while the second addresses the distribution of weather variables, with a focus on their importance in different weeks in relation to the variable to be anticipated. Similarly, indices were calculated for joint effects using weather variable products (two at a time). The model's form is:

$$Y = a_0 + \sum_{i\neq 1}^{p}\sum_{j=0}^{1} a_{ij}\, Z_{ij} + \sum_{i\neq 1}^{p}\sum_{j=0}^{1} b_{ii'j} Z_{ii'j} + e \tag{2}$$

where

$Z_{ij} = \sum_{w=n_1}^{n_2} r_{iw}^{j} X_{iw}$ and $Z_{ii'j} = \sum_{w=n_1}^{n_2} r_{iw}^{j} X_{iw}\, X_{i'w}$

Y: variable to forecast

X: value of i^{th} weather variable in w^{th} week

r_{iw}: correlation coefficient between Y and i^{th} weather variable in w^{th} week

$r_{ii'w}$: correlation coefficient between Y and product of X_i and $X_{i'}$ in w^{th} week

P: number of weather variables considered

n_1: initial week for which weather data were included in the model

n_2: final week for which weather data were included in the model

In some cases, previous disease incidence/pest population (or their indices) and/or the previous year's last population have also been included in the model. Stepwise regression technique was used for selecting important variables to be included in the model. This approach allows for credible warnings at least one week in advance

(Chattopadhyay *et al*., 2005a; Chattopadhyay *et al*., 2005b; Desai *et al*., 2004; Vishwa Dhar *et al*., 2007).

When data is provided for a few years (5-7 years) at varied time intervals (weekly), it is insufficient for building standard models. In this case, the deviation method can be used. It has been considered that the pest population/disease severity at any given moment is determined by the pest's natural life cycle and the meteorological conditions. In order to discover the natural pattern, data from various intervals are averaged across time, and an appropriate model can be established. A model may be fitted with deviations from natural patterns as the dependent variable and weather as the independent variable. Mehta *et al.* (2001) demonstrated this methodology for weekly fruit fly populations in mango at Rehman Khera Farm, Central Institute for Subtropical Horticulture, Lucknow, India.

On the other hand, if historical data is unavailable and only 10-12 data points exist between the time of first appearance of disease/pest and maximum disease severity/pest population, a forecast of maximum disease severity/pest population can be obtained from current season data using a within-year growth model. The technique entails fitting a suitable model to the pattern of disease development/pest population using partial crop season data and forecasting the maximum value based on that model. This technique was used to forecast the percent disease severity (PDS) of Alternaria Blight in the Varuna mustard variety at Kumarganj in 1999-2000 for various sowing dates. The model was,

$$Y_t = A \exp {}^{B}/_{t}\ e \qquad (3)$$

where, t: weeks after sowing, Y_t: percent disease severity at week t, and A and B: model parameters. Using this model, reliable forecasts could be obtained two weeks in advance (Mehta *et al*., 2005).

ARIMA model (Autoregressive Integrated Moving Average)

ARIMA models utilize historical data to identify patterns and trends, making them an effective tool for forecasting in agricultural settings. By analysing factors such as weather patterns, crop health, and pest populations, ARIMA models have the benefit of being able to capture and account for complex temporal patterns and seasonal fluctuations. This makes them ideal for forecasting pest and disease dynamics, which are naturally impacted by a variety of environmental and biological variables (Collier, 2017). The *ARIMA (p, d, q)* model has three parameters. The autoregressive parameter, denoted by parameter p, examines the connection between a variable and its previous occurrences. Through analysing historical data, the autoregressive parameters can be derived to predict future instances of pest and disease occurrences. The second parameter is differentiation (d), and the number of lag forecast mistakes is represented by the running mean value or parameter q. Choosing the right lags is a vital stage in constructing a reliable ARIMA model for forecasting pest and disease outbreaks (Setiyowati *et al*., 2015). Lags indicate the number of past data points considered for predicting future occurrences. The ARIMA model was created using an autocorrelation plot (ACP) on stationary time-series data (Lee & Liu, 2014). The moving average parameter was obtained using the value of the partial correlation coefficient. The moving average segment within the ARIMA model depicts the association between a current observation and the residual error obtained from applying a moving average model to past observations (Mahapatra & Dash, 2020). The created ARIMA model was evaluated by comparing observed data from the farm field with data that the model is anticipated. According to the findings above, *ARIMA (1, 0, 2)* is the best model to forecast the incidence of pests and diseases based on microclimatic data.

Machine learning

Machine learning has shown to be a great revolution in agriculture, transforming many processes to enhance efficiency, production, and sustainability (Chlingaryan *et al*., 2018). From agricultural yield prediction to disease detection, machine-learning approaches have shown enormous promise in revolutionizing agriculture (Priya & Ramesh, 2020). Aerial colour and color-infrared photography have long been used to monitor crop development; however, these technologies are being extensively researched for analysing spatial variability within the field. High-resolution imagery's finer features enable a closer study of crops, allowing for earlier and more accurate diagnosis of stress symptoms, pest infestations, and diseases. This can be critical for making timely interventions and reducing yield losses (Hunt *et al*., 2004). Overall, the use of machine learning in agriculture has resulted in substantial advances and has immense potential for the future (Bestelmeyer *et al*., 2020).

Precision farming is one of machine learning's most successful applications in agriculture, which may give farmers useful insights into improving their irrigation, fertilization, and pest management techniques by analysing data from sensors, satellite photos, and weather predictions (Priya & Ramesh, 2020).

One of the major accomplishments of machine learning models is the detection of agricultural diseases and insect infestations, allowing for early intervention and more effective resource allocation (Maduranga & Abeysekera, 2020). In any crop, pest and disease prediction is a crucial component for the process of managing pests and diseases. Thus, it is necessary to understand the life cycle of the pests and schedule management practices to align with the stages of the pest and pathogen life cycle (Collier, 2017). Machine learning algorithms are becoming more useful in agricultural pest and disease prediction. These algorithms are capable of analysing enormous amounts of data and detecting trends that may indicate pest or disease breakouts (Javaid *et al*., 2023). They can aid in the prediction of possible pest and disease infestations by collecting data on weather patterns, crop health, insect populations, and other relevant aspects (Singh *et al*., 2018). When compared to traditional methods, these systems can greatly increase crop output and quality with reduced pesticide usage.

A study by Bhatia *et al.* (2020) investigates the application of machine learning for identifying tomato pests from images using three classifiers: SVM, k-NN, and DT. Texture features such as GLCM, LBP, HOG, and SURF were utilized, with SVM combined with LBP achieving the best accuracy of 81.02%. The study emphasizes the importance of early pest detection in enhancing tomato crop quality and yield. It showcases the potential of integrating image processing with machine learning to advance agricultural practices.

Pest forewarning and detection utilize a diverse toolbox of methods, and some of the previous studies related to the use of machine learning for pest and disease detection are compiled in Table 1.

Deep learning in object detection

ANNs have emerged as effective tools for solving complicated issues, such as pest prediction in agriculture (Wang *et al*., 2022). Because of its ability to model and analyze deep interactions within big datasets, ANNs are commonly used for crop pest risk prediction. Research has shown that ANNs have good prediction accuracy in anticipating insect populations and assessing their hazards in a variety of crops, including rice. Furthermore, ANNs have been employed in intelligent agent-based prediction systems for pest detection and alert mechanisms, leveraging technologies such as acoustic methods and video processing techniques to allow early pest finding and classification. In pest management, object detection can be used to identify and monitor numerous pests, providing useful information for decreasing their populations and limiting crop loss. Deep learning, a subset of machine learning, has shown significant potential in object detection applications due to its capacity to understand complicated patterns and characteristics from vast datasets (Corrales *et al*., 2015). Digital image processing has seen improvements through deep learning, which is significantly better than conventional techniques. Early pest and disease detection and prediction is made possible by this technology, allowing for prompt intervention and control actions (de Souza *et al*., 2017). Deep learning can be also used in the detection of pests and diseases based on weather data (Pandit *et al*., 2022).

Table 1- Use of machine learning techniques to predict agricultural pests and diseases

Crop	Disease/insect	Algorithm	Data set	Observation	Reference
Mango	Thrips	Random forest	Temperature and humidity	Low error estimates	(Jawade *et al*., 2020)
Rice	Blast	Artificial neural network (ANN)	Temperature and humidity	Average accuracy of 72%	(Jia *et al*., 2020)
Mango	Powdery mildew	Rough sets, linear regression, rough sets based decision, decision tree	Temperature and humidity	Average accuracy of 75%	(Rajni *et al*., 2009)
Rice	Blast	Long-term memory network (LSTM)	Temperature and humidity	Maximum accuracy of 79.4%	(Kim *et al*., 2020)
Coffee	Rust	Fuzzy	Temperature and humidity	Fuzzy models outperformed classical models in terms of error rates.	(Cintra *et al*., 2011)
Pomegranate	General pomegranate diseases	Hidden Markov chain	Temperature, humidity and wind speed	Accuracy of 80.7%	(Pawara *et al*., 2018)
Cherry	A general disease of cherry	Discriminant Analysis	Temperature, humidity, rainfall and wind speed	Maximum prediction accuracy of 93.6%	(Ilic *et al*., 2018)
Tomato	Powdery mildew	Hybrid of support vector machine (SVM), LR	Temperature, Humidity, leaf wetness, wind speed, global radiations	Conducive classes, not conducive classes	(Bhatia *et al*., 2020)
Rice	Blast	ANN, SVM	Evaporation, maximum temperature, minimum temperature, Rainfall, solar radiation, wind speed and humidity	Disease occurrence, disease severity	(Malicdem & Fernandez, 2015)
Potato	Late blight	ELM, SVM	maximum temperature, minimum temperature, maximum humidity, minimum humidity, Rainfall, Number of rainy days	Class 1: <3%, class 2: 4-10%, class 3: 11-30%, class 4: 31-60%, class 5: >60%	(Singh *et al*., 2019)
Orange	Black spot, greening, melonasa, greasy spot, scab, Alternaria brown spot, canker	ACC	Image of Orange, temperature, rainfall, humidity	Disease name	(Kaur & Kaur, 2018)

Olive, Grape	Downy mildew, powdery mildew, peacock spot, anthracnose	ACC	Temperature, humidity, accumulated heat, degree days	Disease occurrence	(Alves *et al.*, 2018)
Cucumber	Downy mildew, leaf spot, anthracnose	Wavelet transformation, SVM	13 variables divided into soil data, weather data, disease data	Disease occurrence (%)	(Junjing *et al.*, 2019)

Convolutional neural network

Convolutional neural networks are leading the way in computer vision problems (Szegedy *et al.*, 2015). Unlike traditional approaches to training classifiers with hand-designed feature extraction, CNNs learn feature hierarchy from pixels to classifier, and train layers simultaneously. Because of the intricacy of the model, CNNs can take weeks to fully train; thus, transfer learning is used to shorten model training by taking a fully trained model for a set of classes and retraining the current weights for additional classes.

One of the primary advantages of CNNs is their capacity to analyze and interpret visual data, which makes them ideal for tasks like plant disease assessment, crop monitoring, and yield prediction (Prashar & Sangal, 2022). CNNs may be taught to detect patterns and abnormalities in photographs of crops, soil, and agricultural landscapes (Zhao *et al.*, 2020). This enables the early diagnosis of pest or disease infestations, as well as prompt action to avoid widespread damage (Ai *et al.*, 2020). Another distinguishing aspect of CNNs is their capacity to process vast amounts of visual data efficiently (Boulent *et al.*, 2019).

Several studies on Machine Learning (ML) techniques used in the agricultural sector focus on the tasks of classification, detection, and prediction of diseases and pests, with a focus on tomato crops (Domingues *et al.*, 2022). In recent years, there has been an increased interest in employing convolutional neural networks to anticipate and detect possible pest and disease outbreaks in tomato crops (Brahmi *et al.*, 2024). To train the Convolutional Neural Network, a dataset was collected from various tomato farms in different regions (Verma & Zhang, 2018). Daily microclimate measurements such as temperature, humidity, and sunlight exposure, along with information on the presence of pests and diseases in the tomato plants were required (Gurle *et al.*, 2019). The data collection process involved collaborating with multiple farms to ensure a diverse and representative dataset for training the model. Additionally, advanced sensors were strategically placed across the farms to capture real-time microclimate data. This ensured that the dataset not only had a wide geographical representation but also captured the dynamic nature of microclimate within each region (Sladojevic *et al.*, 2016). CNNs have shown considerable potential in image recognition and classification tasks, making them an ideal choice for detecting pest and disease indicators in tomato plants (Wiesner-Hanks *et al.*, 2018). The collected data will then be pre-processed to remove any outliers or inconsistencies before being used for training the Convolutional Neural Network (de Souza *et al.*, 2017). Data pre-processing also includes data augmentation techniques such as random contrast, flip, zoom, and rotation to enhance the diversity of the training dataset and prevent overfitting (Shorten & Khoshgoftaar, 2019). A study by Kattenborn et al. (2021) highlights that batch normalization standardivolzes activation function outputs to have a zero mean and unit variance, preventing imbalance caused by extreme activation values. This technique simplifies the gradient descent optimization process, enables the use of larger learning rates, and accelerates network convergence.

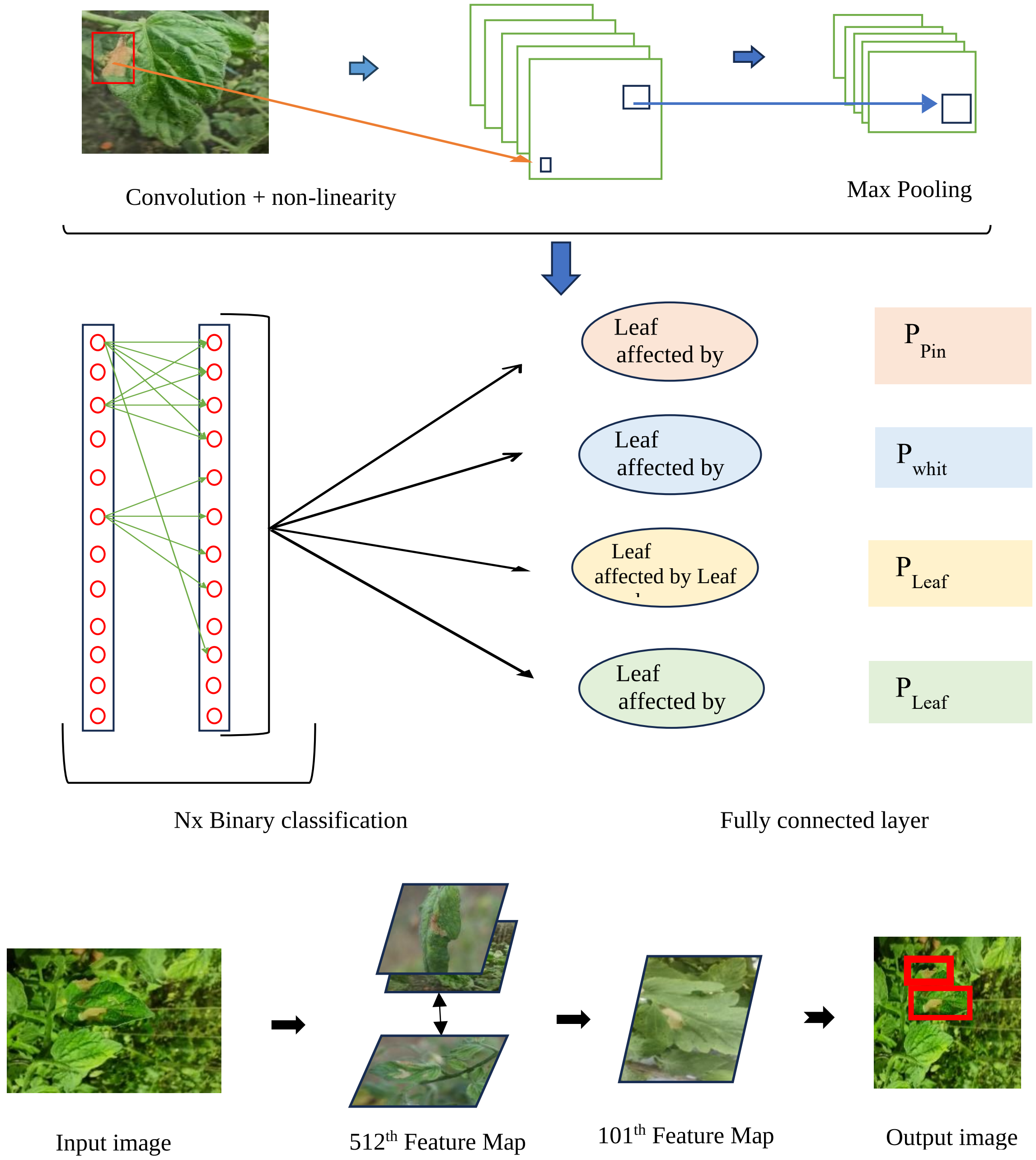

Fig. 3. Architecture of the CNN used for detecting pinworm damage; the input consisted of leaves infected with pinworm, non-linearity includes the activation layer and convolutional layer filters the input images and reduces the size of the dataset

The training process involved splitting the dataset into training, validation, and testing sets to evaluate the performance of the model. Various hyperparameters were tuned, and different architectures were explored to optimize the CNN for accurate pest and disease forewarning (López-Morales *et al.*, 2008). The CNN was trained to automatically extract features from the raw microclimate data and correlate them with the presence of pests and diseases in the tomato plants (Brahimi *et al.*, 2017). Training a CNN on a varied collection of tomato plant photos, including healthy and diseased plants, may lead to a powerful forewarning system (Kamilaris & Prenafeta-Boldú, 2018). To accomplish this goal, the researchers first compiled a broad collection of tomato plant photos, including those displaying healthy plants as well as those damaged by numerous pests and diseases (Nihar *et al*., 2021). This dataset will be critical in training the convolutional neural network to recognize and categorize various signs and manifestations of pests and diseases in tomato (Paymode *et al*., 2021). Once the dataset is produced, it will begin training the CNN, using approaches like data augmentation to improve the model's capacity to generalize and predict on previously unknown data (Jia *et al*., 2020). The model will be validated and fine-tuned to guarantee that it is successful in detecting possible pest and disease outbreaks. Through the training and evaluation process, the developed CNN models showed satisfactory performance in detecting nine different tomato diseases and pests. (David, 2023). The CNN models achieved a high accuracy rate of 99.18% in classifying the presence of pests and diseases based on the microclimate data. This high accuracy rate outperformed previous shallow models and demonstrated the effectiveness of using Convolutional Neural Networks for pest and disease forewarning in tomato plants (Emebo *et al*., 2019). The results of this study highlight the potential of using deep learning and Internet of Things technologies, specifically convolutional neural networks, for accurate and efficient pest and disease forewarning in tomato plants (Gonzalez-Huitron *et al*., 2021). This approach provides farmers with a practical tool to remotely monitor the health of their tomato plants, reducing effort and enabling timely interventions (Agarwal *et al*., 2020). Once the model was trained, it underwent rigorous testing and validation to assess its ability to accurately predict pest and disease occurrences based on the microclimate data (Prajwala *et al*., 2018). The results of the training and validation process were crucial in determining the effectiveness and reliability of the CNN for forewarning pest and disease outbreaks in tomato plants (de Souza *et al*., 2017). Farmers will get this pest and disease warning information and advice on proper crop management techniques via electronic media, such as the Internet, short messaging service (SMS) and other digital platforms (Hughes & Salathé, 2015).

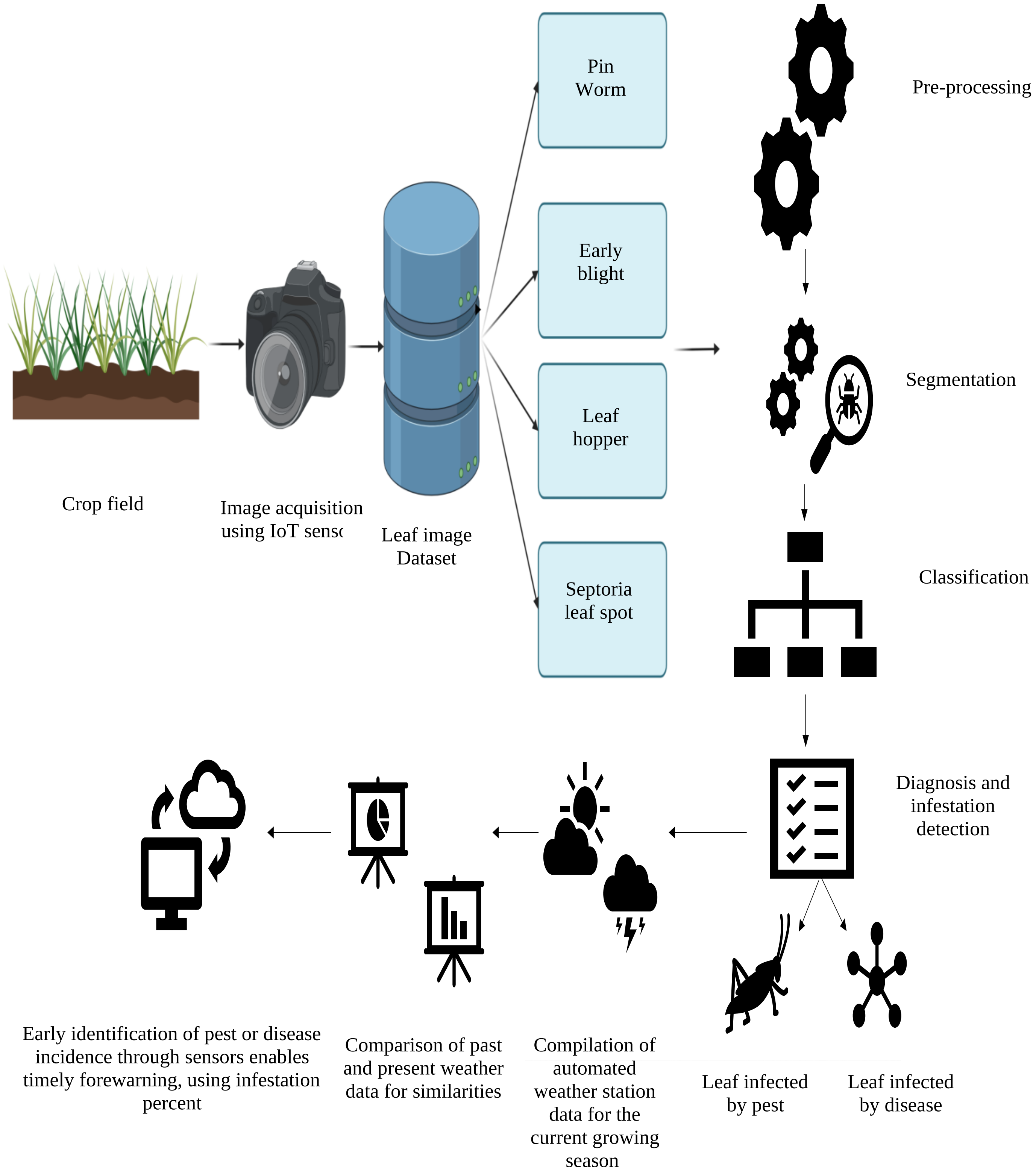

Fig. 4. Pest and disease forewarning using convolutional neural network

Recurrent-CNN

Girshick et al. (2014) proposed R-CNN as a method for efficient object localization in object identification. R-CNN uses the selective search algorithm. The initial step in deploying R-CNN for agricultural crops is to gather and preprocess the dataset. This involves acquiring photos of numerous crops, including wheat, rice, maize, and soybeans, from diverse agricultural areas (Qi *et al.*, 2023). The collection should also contain photographs of prevalent pests and diseases that attack these crops (Barbedo, 2020). Once the photos have been acquired, they must be pre-processed to ensure that they are in the correct format for training the R-CNN model. This might include scaling the photographs, normalizing pixel values, and labelling them with bounding boxes to show the location of crops, pests, and diseases. Following the preparation of the dataset, the R-CNN model is trained. A convolutional neural network is used to extract features from the pictures, followed by a region proposal network to provide plausible bounding boxes for objects in the images. The model is then trained to categorize the items that fall inside the suggested boundaries (Patel & Bhatt, 2021). Once trained, the model must be assessed against a different testing dataset to determine its accuracy and performance. Following assessment, the model may be used to detect and analyze crops, pests, and diseases in agricultural settings (Zheng *et al.*, 2019).

Fast R-CNN

Fast R-CNN was created to address the computational inefficiencies of R-CNN. Unlike R-CNN, which processes each region proposal separately via CNN, fast R-CNN uses the whole picture and its region suggestions as input in a single forward pass through the CNN architecture. This considerably minimizes the processing overhead. Furthermore, fast R-CNN combines numerous architectural components, such as ConvNet, RoI pooling, and classification layers, into an organised and efficient framework. One of the primary benefits of adopting fast R-CNN in agriculture is its capacity to reliably identify regions that need attention, allowing for focused treatments while minimizing total input consumption such as pesticides and herbicides (Sykes *et al.*, 2023). One of the primary benefits of adopting Fast R-CNN in agriculture is its ability to recognize items of interest in pictures quickly and accurately (Halstead *et al.*, 2018). This allows farmers to immediately detect and rectify potential issues in their fields, resulting in better crop management and higher yields (Qiang *et al.*, 2020).

Faster R-CNN

Faster R-CNN, proposed by Ren et al. (2015), overcomes the bottleneck of selective search in its predecessor by including a region proposal network. After running the picture through a backbone network, it generates convolutional feature maps. The area proposal network then uses these feature maps to create anchors, which represent the centres of sliding windows of various sizes and scales. These anchors are then processed by the classification layer, which determines object functioning, and the regression layer, which localizes the bounding boxes. This method substitutes selective search, considerably increasing object detection efficiency by including region proposal creation into the network design.

Recently, a smartphone application called "PESTPREDICT" which uses weather-based pest warnings as part of integrated pest management for crop protection was developed. This program helps farmers, agricultural extension workers, and researchers obtain location-specific predictions of desired pest or disease for target crops so that they may be effectively managed (Szegedy *et al.*, 2015). Plantix is an influential software that is gaining popularity among farmers and gardeners. Its key characteristics include plant disease diagnosis, pest detection, and gardening recommendations (Siddiqua *et al.*, 2022). The app uses picture recognition technology to identify plant pests and diseases, giving users precise information and treatment recommendations (Petrellis, 2017). In addition to its diagnostic capabilities, Plantix functions as an information platform for plant enthusiasts, providing articles, videos, and other materials to assist users in taking care of their plants. Plantix has become an indispensable tool for anybody who wants to keep their plants healthy and developing (Mrisho *et al*., 2020). In this study by Lin et al. (2020), Faster Region-Convolutional Neural Networks (Faster R-CNN) and Mask R-CNN were utilized to create a knowledge-based system capable of automatically identifying plant pests and diseases. The Faster R-CNN achieved a regional recognition accuracy of 89%, while the Mask R-CNN demonstrated an area recognition accuracy of 81%. This research successfully developed a system for pest and disease identification.

YOLO (You Only Look Once)

The YOLO approach to object detection revolutionizes the process by enabling simultaneous identification and localization of objects in an image at a single glance. Unlike traditional multi-step methods, YOLO redefines object detection as a regression problem, directly predicting spatially separated bounding boxes and their corresponding class probabilities. This is achieved through a single neural network evaluation, making the process efficient and streamlined (Du, 2018). A specialized tomato-picking robot is designed exclusively for use in facility agriculture environments. A deep learning-based recognition technique is implemented. The process identifies the positions of peduncles by connecting bounding boxes and acquires depth data using a depth camera. It then simulates manipulator trajectory planning based on spatial coordinates, overcoming challenges like lighting variations and obstructions. YOLO outperforms the SSD algorithm with higher accuracy and confidence in tomato shape detection. Future studies could adapt this approach to other crops like eggplants, cucumbers, and oranges with contrasting features (Zhaoxin *et al*., 2022).

Boons

Large data sets can be analyzed by machine learning algorithms, which can spot patterns and trends that are invisible to the human eye (Gauriau *et al*., 2024). This makes it possible for agriculture specialists to more precisely forecast and warn of impending outbreaks of pests and diseases (Ifft *et al*., 2018). Machine learning models can provide early warnings by utilizing environmental conditions, historical data, and crop health indicators. This enables farmers to take proactive actions to reduce the impact of pests and diseases on their crops (Veeragandham & Santhi, 2020). Farmers can save a large amount of money by utilizing machine learning to forecast pests and diseases. Farmers can decrease the needless use of chemical pesticides and fertilizers, resulting in lower costs and more sustainable agricultural practices, by precisely anticipating and diagnosing potential dangers to their crops (Bestelmeyer *et al*., 2020). Farmers can also reduce crop losses and guarantee a more consistent and dependable production by using preventative measures based on machine learning insights, which will further contribute to agriculture's long-term sustainability (Rehman *et al*., 2019). Based on the unique requirements and conditions of each farmer's crop, machine learning algorithms can offer customized recommendations and decision support (Ahmed *et al*., 2024). These algorithms can adjust and improve their recommendations by evaluating real-time data and continuously learning from new information, accounting for fluctuations in crop types, weather, and soil conditions (Sudduth *et al*., 2020). With this degree of individualized support, farmers are better equipped to manage pests and diseases, and make well-informed decisions that improve crop output and health (Benos *et al*., 2021).

Conclusion

Overall, the implementation of microclimate-based pest and disease warning systems in tomato agriculture has the potential to transform the way farmers manage their crops. This technique enables farmers to make educated choices by using real-time data and advanced analytics, resulting in more effective pest and disease management strategies. It minimizes pesticide use, and also promotes sustainable agriculture practices and crop quality. More research and technical improvements will improve the accuracy and reliability of microclimate-based forewarning systems. This will allow for greater adoption across areas and crop kinds, eventually improving agricultural production and environmental sustainability. As the agricultural industry evolves, adopting novel solutions such as microclimate-based forewarning will be critical in tackling pest and disease concerns, resulting in a more resilient and productive agricultural sector. In addition, incorporating microclimate-based pest and disease forewarning into tomato growing might provide farmers with economic advantages. Farmers may be able to boost their total production and revenues by lowering their reliance on pesticides and crop loss. This, in turn, may help ensure the long-term profitability of agricultural enterprises and the livelihoods of rural communities. Furthermore, as technology advances and these systems become more accessible and user-friendly, it is expected that small-scale farmers will be able to utilize the advantages of microclimate-based forewarning, democratizing access to effective pest and disease control tools.

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مقاله مروری

مروری بر یادگیری ماشین برای تشخیص آفات گوجه‌فرنگی

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چکیده

تاثیر یک مولفه جوی یا متغیر هواشناسی بر میزبان، پاتوژن یا تعامل آن‌ها در محیط‌های کنترل‌شده، بخش عمده‌ای از تاثیر تغییرات اقلیمی بر آفات و بیماری‌های گیاهان را به خود اختصاص داده است. تغییرات اقلیمی می‌تواند منجر به تغییراتی در مراحل و سرعت رشد آفات و بیماری‌ها، مقاومت میزبان و فیزیولوژی تعاملات میزبان–پاتوژن یا میزبان–آفت شود که می‌تواند باعث آسیب قابل‌توجه و کاهش عملکرد محصول گوجه‌فرنگی گردد. در سال‌های گذشته، رویکردهای مختلف در پیش‌بینی دقیق آفات و بیماری‌ها ناموفق بوده‌اند. ولی پیشرفت قابل‌توجه در شبکه‌های عصبی کانولوشن عمیق (DCNN)، باعث ایجاد انقلابی در تشخیص زودهنگام آفات و بیماری‌ها در محصولات کشاورزی شده است. این مدل‌های هوش مصنوعی با تجزیه و تحلیل مقادیر زیادی از داده‌های اقلیمی حال حاضر و گذشته، در کنار شناسایی اشیا و طبقه‌بندی تصاویر، می‌توانند شیوع بیماری‌ها را با دقت چشمگیری پیش‌بینی کنند. با این حال، درک ریزاقلیم خاص مناسب برای هر آفت و بیماری برای مداخله موثر بسیار مهم است. ترکیب دو عنصر داده‌های اقلیمی با پردازش تصویر، یک رویکرد قدرتمند و هدفمند برای حفاظت از محصولات ایجاد می‌کند. یک سیستم هشداردهنده می‌تواند به کاهش استفاده از آفت‌کش‌ها کمک کند و در نتیجه هزینه تولید محصول و آلودگی محیط‌زیست را کاهش دهد. برای پیش‌بینی بهتر آفات و بیماری‌ها در شرایط مختلف، باید از سرورهای ابری مناسب و شبکه‌های حسگر مبتنی بر اینترنت اشیا استفاده کرد.

واژه‌های کلیدی: CNN، پیش‌بینی آفات، خرد اقلیم، گوجه‌فرنگی، یادگیری ماشین

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