International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 28, No. 1, February, 2023, pp. 133-140
Journal homepage: http://iieta.org/journals/isi

Pesticide Recommendation for Different Leaf Diseases and Related Pests Using Multi-Dimensional Feature Learning Deep Classifier

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https://doi.org/10.18280/isi.280113

Received: 22 September 2022
Accepted: 20 November 2022

Keywords:
leaf diseases, PDATFEGAN, MFL-DCNN, pesticide, fuzzy rule, rough set, intuitionistic fuzzy approximation space, recommendation system

ABSTRACT

In agricultural applications, the most essential task is to classify leaf diseases and their associated pests from various aspects. To achieve this, a Deep Convolutional Neural Network (DCNN) model was developed to classify the leaf diseases based on the soil and climatic features. But it needs a recommendation system to control the pesticide use for controlling the leaf diseases caused by specific pests. Hence, this paper hybridizes the Multi-dimensional Feature Learning-based DCNN (MFL-DCNN) with the Rough Set (RS) on an intuitionistic Fuzzy approximation space (RSF)-based decision support system to suggest the proper pesticides for a certain crop to be planted in a particular region. First, the leaf images are augmented by the Positional-aware Dual-Attention and Topology-Fusion with Evolutionary Generative Adversarial Network (PDATFEGAN) model. Then, the multi-dimensional data such as the created leaf images, pest, soil, weather, and pesticide data are fed to the DCNN with a softmax classifier for classifying leaf diseases and related pests. Then, the RSF-based decision model is applied, which determines the correlation between leaf disease and pests to recommend suitable pesticides. Finally, the experimental results reveal that the MFL-DCNN-RSF accomplishes a maximum efficiency than all other models for recommending pesticides to control leaf diseases and pests.

1. INTRODUCTION

Crop productivity is endangered by many conditions, like environmental issues, crop diseases, and land erosion. The pathogenic illnesses of plants are worsened due to the growth of a wide range of natural commodities, and environmental degradation characteristics [1, 2]. Those illnesses are not appropriately recognized and diagnosed by human eyesight, which impacts yield productivity. To tackle this issue, Artificial Intelligence (AI) models including machine learning and deep learning algorithms have been adopted in crop/plant disease detection [3, 4]. The crop diseases are mostly identified by the leaves using a variety of methods. Many researchers have experienced the different machine learning algorithms for the detection and classification of various plant leaf diseases, including Support Vector Machine (SVM), Artificial Neural Network (ANN), random forest, and so on [5, 6]. But these algorithms need separate mechanisms for each process like pre-processing, feature extraction, feature selection, and classification. This leads to high computational time complexity.

So, deep learning algorithms have been developed for the detection and classification of crop leaf diseases from a huge number of images. Mostly used deep learning algorithms are pre-trained DCNNs [7-9], e.g., VGG, AlexNet, GoogleNet, etc. These algorithms achieved better feasibility and efficiency in identifying and classifying leaf diseases. Alternatively, images captured from farms were blurred. Poor image quality may degrade the accuracy of pre-trained classifiers, which were trained on clear high-resolution images. To increase the accuracy of leaf disease classification, low-resolution images should be regenerated into high-resolution images. For this purpose, a variety of Generative Adversarial Network (GAN) models has been employed [10], which generate more high-resolution images from the limited number of low-resolution images. Amongst, the GAN with the Dual-Attention and Topology-Fusion strategies called the DATFGAN model [11] outperformed classical GAN models in terms of sharpness and image details. It can generate sharper leaf disease images precisely by eliminating artifacts or noisy textures for increasing classification accuracy. The generated high-resolution leaf disease images were classified by the different pre-trained DCNN models to identify the types of diseases. In our previous works, the problems in the DATFGAN were solved: (a) the spatial correlation among the training images was learned with the position of disease region from the partial or whole leaf by the Positional-aware DATFGAN (PDATFGAN) model [12], and (b) the non-convergent iteration and adversarial learning ability were further improved by the Positional-aware Dual-Attention and Topology-Fusion with Evolutionary Generative Adversarial Network (PDATFEGAN) model which adopts an Evolutionary GAN (EGAN) [13]. The EGAN considers many adversarial objective values to reduce the different errors observed between the distribution of created and actual images. But the classification of leaf diseases was not only effective to enhance crop productivity.

Identification of causes for leaf diseases was also essential to control both pests and their related diseases efficiently. So, a few researchers focused on identifying pests from the leaf pest images [14, 15] of different plants using deep learning models. But, additional factors like soil and weather attributes were necessary to identify the pests that have more responsibility for a particular leaf disease. Also, there were no proper pesticide recommendation systems to advise farmers to use proper pesticides for controlling pests and leaf diseases.

Therefore, the MFL-DCNN-RSF model is proposed to control pests and leaf diseases by suggesting the proper pesticides. It enables a proper decision to predict the pesticide for a specific crop to be cultivated in a certain region having different soil and climate features. The RSF strategy is adopted to create the rule for recommending pesticides regarding multi-dimensional data such as crop, climate, soil, leaf diseases, and pests. Based on the created rules, the correlation between these characteristics is identified to suggest the proper pesticide to control leaf diseases and pests. Thus, this MFL-DCNN-RSF model can be helpful for cultivators to use proper pesticides for specific leaf diseases to improve crop productivity.

The remaining sections are prepared as follows: Section 2 discusses various recommendation systems used in agricultural activities. Section 3 describes the MFL-DCNN-RSF model and Section 4 demonstrates its competence. Section 5 summarizes the complete research and gives further enhancement.

2. LITERATURE SURVEY

Pinki et al. [16] designed an automated model using K-means clustering and the SVM to diagnose the different paddy leaf infections. Also, insect repellents were recommended based on the infection severity. But this model was not effective to classify multiple diseases simultaneously. Kosamkar et al. [17] developed a model, which performs preprocessing and feature extraction of leaf images followed by CNN to classify the diseases and recommend pesticides. But it needs other factors, which also affect the leaves.

Tetila et al. [18] analyzed various CNN frameworks for classifying the soybean pest images. However, it has a high learning time and less robustness. Rahman et al. [19] designed an enhanced 2-level training-based compact CNN model to recognize leaf infections and pests from the rice crop images. But it requires climate and soil features to improve the efficiency of automatically identifying pests. Ayan et al. [20] developed a genetic algorithm-based weighted ensemble of different pre-trained DCNN models using the sum of maximum probabilities mechanism to classify the crop pests properly. But its efficiency was less for large-scale datasets.

Wang et al. [21] developed a new DeepPest using an attention strategy for the primary categorization of insect photos into plant types. But, it has less efficiency when a small number of pest images were trained. Escola et al. [22] designed the SVM for the identification of cicadids in coffee trees. But it has a high maintenance cost and needs a recommendation system to suggest pesticides. Rao et al. [23] developed the AlexNet for automatically identifying grapes and mango leaf infections. But it needs to classify more classes of leaf infections and a recommendation system to suggest the proper solution to diagnose that infection.

Table 1. Comparison of different existing models

Ref. No.	Algorithm used	Problem solved	Merits	Demerits
[16]	K-means clustering and SVM	Paddy leaf disease classification	It can suggest pesticides based on the disease severity.	It was not effective to classify multiple diseases simultaneously.
[17]	CNN	Leaf disease classification and pesticide recommendation	Better accuracy to suggest pesticides	It needs climate and soil factors to increase accuracy.
[18]	CNN	Soybean pest classification	It can control pests in soybean fields.	It has a high learning time and less robustness.
[19]	2-level training-based compact CNN	Rice leaf disease and pest recognition	Highest accuracy	It requires climate and soil features to improve efficiency.
[20]	Genetic algorithm-based weighted ensemble DCNN	Crop pest classification	It can recognize pests earlier and suggest suitable pesticides.	Its efficiency was less for large-scale datasets.
[21]	DeepPest using attention strategy	Pest classification	High robustness	It has less efficiency when for a small-scale dataset.
[22]	SVM	Cicadids recognition	Better accuracy	It has a high maintenance cost and needs a recommendation system to suggest pesticides
[23]	AlexNet	Grapes and Mango leaf disease classification	Low cost and high accuracy	It needs to classify more classes of leaf infections and suggest the proper solution to diagnose that infection.
[24]	Tiny-YOLOv3	Pest classification	It lowers pesticide costs and decreased environmental damage.	More climatic features were needed to enhance efficiency.
[25]	OSSL	Pest recognition	It can prevent the contamination of a training dataset.	It needs to control the pests by recommending pesticides.
[26]	Pre-trained CNNs and SVM	Crop disease and pest classification	Highest accuracy	It takes more time due to more features.
[27]	VGG	Multi-crop leaf disease classification	Greater accuracy	It needs to apply advanced CNN structures.

Chen et al. [24] developed a Tiny-YOLOv3 model to recognize fruit tree pests. In contrast, several climatic features were needed to enhance efficiency. Rustia et al. [25] designed an Online Semi-Supervised Learning (OSSL) for an automated insect pest forecasting model. But it needs to control the pests by recommending pesticides. Turkoglu et al. [26] presented CNN and SVM classifiers to identify crop disease and pests. But it takes more time due to a large number of features. Paymode and Malode [27] employed the VGG model to identify the multi-crops leaf infection. But it needs to apply advanced CNN structures to achieve a deep analysis of leaf images.

Table 1 summarizes various models according to the algorithms used, problem solved, merits, and demerits. According to this summary, it is addressed that most of the models focused on pest and leaf disease classification, whereas a pesticide recommendation is essential to prevent pest and leaf diseases efficiently. So, this research develops a new recommendation system, which suggests pesticides to control environmental damages due to the use of excessive or improper pesticides.

3. PROPOSED METHODOLOGY

The MFL-DCNN-RSF model for recommending suitable pesticides based on the classification of leaf diseases and pests is explained briefly. Figure 1 depicts the overall representation of the presented model for classifying the leaf diseases with their related pests and predicting the proper pesticide.

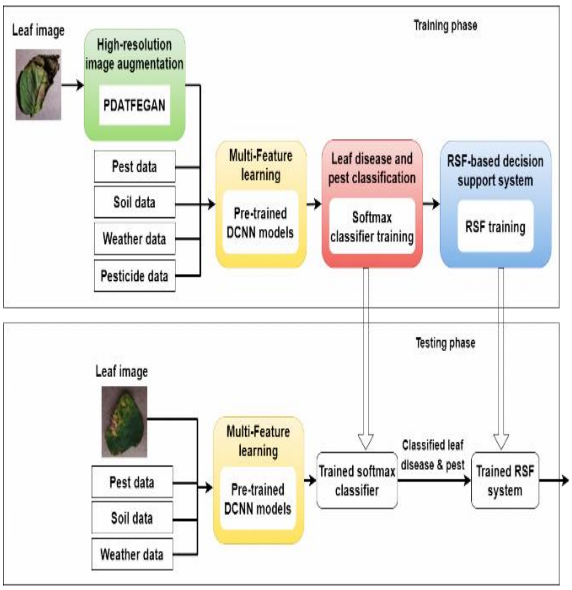

Figure 1. Schematic overview of MFL-DCNN-RSF for pesticide recommendation

3.1 Leaf images and pest data collection

To begin, the PlantVillage Dataset (PVD) [28] is used to collect leaf infection images for 3 different plants: tomato, bell pepper, and potato plants. There are 20636 images in this dataset, which are divided into 15 categories: pepper-bell bacterial spot, pepper-bell healthy, potato early blight, potato late blight, potato healthy, tomato bacterial spot, tomato early blight, tomato late blight, tomato leaf mold, tomato septoria leaf spot, tomato 2-spotted spider mites, tomato target spot, tomato yellow leaf curl virus, tomato mosaic virus and tomato healthy. This PVD includes images of several types of leaf infections that can impact tomato, pepper, and potato plants. Those images are in the RGB color space and saved in the uncompressed JPG format.

Once those images are obtained, the PDATFEGAN model is used to generate super-resolution micro patches for all leaf images, which are fused to provide complete super-resolution leaf images. In addition to the leaf images, a dataset is formed, which contains the agricultural pests related to the given 12 classes of leaf diseases. In this dataset, 10 insect pests are included with the related leaf diseases and weather situations in the region of the Coimbatore district in Tamilnadu. Maximum Temperature (T_{max}), Minimum Temperature (T_{min}), Relative Humidity (RH) in the morning and evening, Rainfall (RF), Wind Speed (WS), and Sun-Shine Hours (SSH) are among the time series of weather features evaluated in the occurrence of pests. Tomato mosaic virus, Tomato leaf curl virus, Xanthomonas campestris, Alternaria solani, Phytophthora infestans, Corynespora cassiicola, Xanthomonas gardneri, Alternaria tomatophila, Passalora fulva, Septoria lycopersici, and Tetranychidae are among the pests associated with the given 12 classes of leaf diseases and those pest data are addressed for the different climatic features.

3.2 Training of the MFL-DCNN classifier

Once all these data are obtained, the MFL-DCNN classifier is trained to classify the leaf diseases and their related pests. The learning of the MFL-DCNN classifier is shown in Figure 2, wherein the DCNN consists of 3 different pre-trained structures such as ShuffleNetV2, DenseNet121, and MobileNetV2.

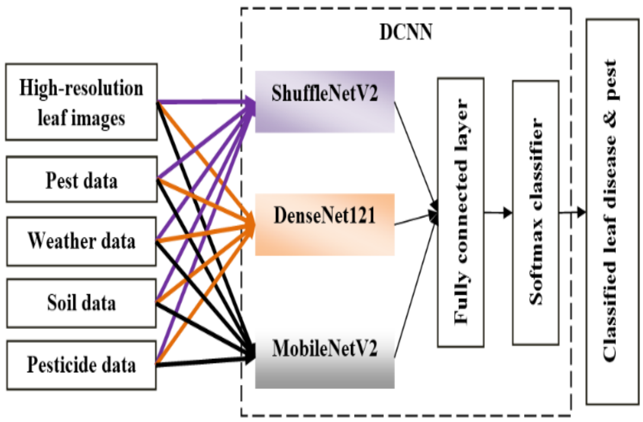

Figure 2. Learning of MFL-DCNN classifier

After classification, it is needed to recommend the proper usage of pesticides to control leaf diseases efficiently. So, a pesticide dataset is created, which contains 12 classes of pesticides like copper hydroxide, resistant cultivators, etc. Similarly, soil features such as pH, moisture, and availability of nutrients (e.g., nitrogen (N), phosphorus (P), and potassium (K)) are collected as a soil property dataset. Both pesticide and soil datasets are collected around the Coimbatore district in Tamilnadu, from November 2021 to May 2022. Table 2 presents a few examples of pesticides used for leaf diseases with their related pests, soil, and weather factors.

Table 2. Examples of pesticides used for different leaf diseases, pests, soil and weather factors

Leaf Disease Name	Pest Name	Soil & weather factors	Pesticide Name
Pepper bell bacterial spot	Xanthomonas campestris	High temperature, high RH, low pH, low nutrients	Cuprofix
Potato Early blight	Alternaria solani	High WS, high RH, high temperature, low pH, low nutrients	Maneb
Potato late blight	Phytophthora infestans	High moisture, low pH, low nutrients	Mancozeb
Tomato target spot	Corynespora cassiicola	High moisture, high RH, low nutrients	Azoxystrobin
Tomato mosaic virus	Tomato mosaic virus	High temperature, low pH, low nutrients	Sulfoxaflor
Tomato yellow leaf curl virus	Tomato leaf curl virus	High temperature, low pH, low nutrients	Pyrafluquinazon
Tomato bacterial spot	Xanthomonas gardneri	High temperature, high RH, low pH, low nutrients	BASF Cabriotop
Tomato early blight	Alternaria tomatophila	High WS, high RH, high temperature, low pH, low nutrients	Bonide Liquid Copper
Tomato late blight	Phytophthora infestans	High mositure, low pH, low nutrients	Clutch
Tomato leaf mold	Passalora fulva	High temperature, high RH, low pH, low nitrogen	Spray chlorothalonil
Tomato septoria leaf spot	Septoria lycopersici	Medium temperature, high RH, high RF, low pH, low nutrients	Copper soap
Tomato two spotted spider mite	Tetranychidae	High temperature, low RF, low RH, low pH, low nutrients	Bifenthrin

3.3 Pesticide decision support and recommendation system

To recommend suitable pesticides, the RSF-based decision support model is proposed. The primary tasks in this RSF system as illustrated in Figure 3 are fuzzification, RSF inference engine training and testing.

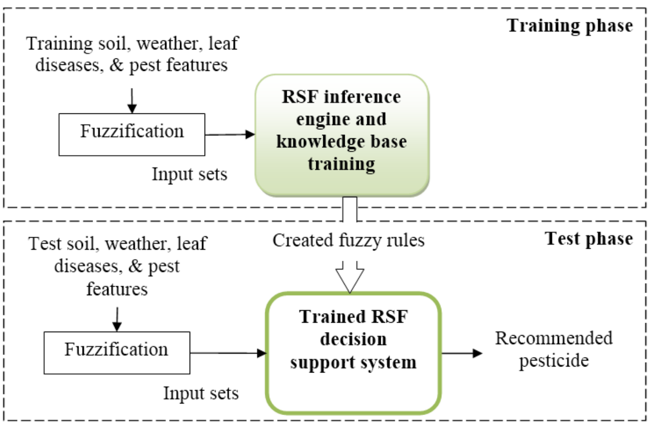

Figure 3. Major processes in RSF decision support system

First, a fuzzy set is defined, which gives various degrees of the membership function for its elements in the range of (0, 1). A fuzzy set is an extension of a crisp set, which allows only full membership or no membership, whereas fuzzy set allows partial membership. The list of multi-dimensional data created the fuzzy set as:

$$X = \{temperature, \ldots, N, P, K,\} \tag{1}$$

Then, a membership function defines how each element in the input space is mapped to a membership value (or membership degree) between 0 and 1. The membership function maps all elements of X to a membership value between o and 1 as:

$$\mu(x) = \{High, Moderate, Low\} \tag{2}$$

3.3.1 RSF System

Consider $U \neq \varphi$ is a quasi finite group of topics known as space and x is a specific component of U. An Intuitionistic Fuzzy Set (ISF) X of U is described as $\{x, \mu_X(x), v_X(x)\}$, where $\mu_X: U \to [0,1]$ and $v_X: U \to [0,1]$ is the membership and non-membership degree, correspondingly, for all components $x \in U$ such that $0 \leq \mu_X(x) + v_X(x) \leq 1$. The range $\pi_X(x) = 1 - (\mu_X(x) + v_X(x))$ is known as the indecision component that can provide either membership or non-membership or both ranges. Specifically, $(\mu_X(x), v_X(x))$ is utilized to define the ISF X.

An intuitionistic fuzzy association (IA) on U is an ISF represented on (U×U) represented using the membership μ_{IA} and the non-membership v_{IA} in Eq. (3).

$$IA = \{(\mu_{IA}(x_i, x_j), v_{IA}(x_i, x_j)) \mid x_i, x_j \in U\} \tag{3}$$

An IA on U is called an intuitionistic fuzzy neighborhood association when it ensures the below criteria, where $\mu_{IA}(x_i, x_j)$ is the membership degree and $v_{IA}(x_i, x_j)$ is the non-membership degree among 2 features x_i and x_j.

1. $\mu_{IA}(x_i, x_j) = 1$ and $v_{IA}(x_i, x_j) = 0$ for each $x_i \in U$.
2. $\mu_{IA}(x_i, x_j) = \mu_{IA}(x_i, x_j)$ and $v_{IA}(x_i, x_j) = v_{IA}(x_i, x_j)$ for each $x_i, x_j \in U$.

Consider $J = \{(\alpha, \beta) | \alpha, \beta \in [0,1]\}$ and $0 \leq \alpha + \beta \leq 1$. After, for any $(\alpha, \beta) \in J$, (α, β)-cut is provided as $IA_{\alpha,\beta} = \{(x_i, x_j) | \mu_{IA}(x_i, x_j) \geq \alpha \ and \ v_{IA}(x_i, x_j) \leq \beta\}$. It is observed that the 2 features x_i and x_j are (α, β)-similar to IA, when $(x_i, x_j) \in IA_{(\alpha,\beta)}$ and $x_i IA_{(\alpha,\beta)} x_j$ is defined. Two features x_i and x_j are called (α, β)-matching to IA, when a series of components $u_1, u_2, \ldots, u_n$ presents in U such that $x_i IA_{(\alpha,\beta)} u_1, u_1 IA_{(\alpha,\beta)} u_2, \ldots, u_n IA_{(\alpha,\beta)} x_j$. In this scenario, it is observed that x_i is a uniformity association $IA_{(\alpha,\beta)}$. The $IA_{(\alpha,\beta)}$-uniformity class of a component x in U is defined as $[x]_{(\alpha,\beta)}$. The pair $K = (U, IA(\alpha, \beta))$ is known as IF approximation space.

Consider $X \subseteq U$. Then, (α, β)-minimum and (α, β)-maximum approximation of X in the generalized approximation space K=(U, IA(α, β)) is defined as $(X_{Min}^{\alpha,\beta}, X_{Max}^{\alpha,\beta})$ in Eqns. (4) & (5):

$$X_{Min}^{\alpha,\beta} = \cup \{Y | Y \in IA_{\alpha,\beta}^* \ and \ Y \subseteq X\} \tag{4}$$

$$X^{\alpha,\beta}_{Max} = \cup \left\{ Y \middle| Y \in IA^{*}_{\alpha,\beta}\ and\ Y \cap X \neq \varphi \right\} \tag{5}$$

A given set X is known as (α, β)-rough when $X^{\alpha,\beta}_{Max} \neq X^{\alpha,\beta}_{Min}$. Similarly, a given set X is known as (α, β)-crisp when $X^{\alpha,\beta}_{Max} = X^{\alpha,\beta}_{Min}$. Evenly, a set X is known as (α, β)-rough when the limit $LIM^{\alpha,\beta}_{IA} = X^{\alpha,\beta}_{Max} - X^{\alpha,\beta}_{Min}$ such that $LIM^{\alpha,\beta}_{IA} \neq \varphi$.

3.3.2 Fuzzification

In this task, a crisp input is converted into a lingusitic variable using the membership function provided by the fuzzy knowledge base. The triangular membership function is used because the linguistic variables are modeled into 3 sets i.e., all the elements in X are converted into Low (L), Medium (M), and High (H). This process needs to get input provided by the user. The compositional ranges of multi-dimensional data are great determinants for predicting suitable pesticide. Such multi-dimensional data are grouped into 3 linguistic variables in the range of 0 to 1 (as illustrated in Table 3).

Table 3. RSF-based decision input variables (for weather and soil attributess)

Attributes	Low (L)	Moderate (M)	High (H)
Temperature	0–35	36–65	66–100
RH	0–29	30–59	60–80
RF	0–40	41–70	70–100
WS	15–30	30–69	70–100
SSH	0.2–0.45	0.46–0.7	0.71–1.0
Soil moisture	10–25	25–40	40–60
pH	0.1–0.3	0.3–0.6	0.6–1.0
Nitrogen (N)	1.0–1.99	2.0–3.99	4.0–6.0
Phosphorous (P)	0.15–0.35	0.36–0.59	0.60–0.80
Pottasium (K)	0.1–2.49	2.50-4.49	4.50–8.50

3.3.3 Membership and non-membership calculation

The intuitionistic fuzzy tolerance finds the maximum indiscernibility of all attributes. The RSF generates (α, β) uniformity classes, where α refers to the membership degree and β refers to the non-membership degree, correspondingly. The membership degree should be large and the non-membership degree should be small to obtain a better prediction of proper pesticides.

Because each prediction can include accurately a particular pesticide, the model fails to analyze the data if belongingness is set to 1 and non-belongingness is set to 0. It is due to the feature values being non-qualitative. The membership and non-membership associations are calculated such that the total ranges obtain from 0 to 1 and such factors should be symmetric.

Here, pesticide prediction is performed using the different features related to leaf diseases, pests, soil, and climatic conditions. By changing the values of α and β, these features may diverge from each other. The range of α is decremented and the range of β is incremented, gradually the number of features will become more essential. The membership degree (μ) and the non-membership degree (v) amid x_i and x_j are described in Eqns. (6) & (8), respectively:

$$\mu_A(x_i, x_j) = 1 - \frac{\left| V^{x_i}_{a_i} - V^{x_j}_{a_i} \right|}{\max(V_{a_i})} \tag{6}$$

$$v_A(x_i, x_j) = 1 - \frac{\left| V^{x_i}_{a_i} - V^{x_j}_{a_i} \right|}{2 \times \max(V_{a_i})} \tag{7}$$

In Eqns. (6) & (7), $V^{x_i}_{a_i}$ denotes the value of x_i for a particular crop a_i.

Table 4. Sample rules for pesticide recommendation

Temperature	RH	RF	WS	SSH	Soil moisture	pH	N	P	K	Leaf diseases	Pests	Pesticide
H	H	L	M	H	L	L	L	L	L	Pepper bell bacterial spot	Xanthomonas campestris	Cuprofix
H	H	L	H	M	H	L	L	L	L	Potato Early blight	Alternaria solani	Maneb
L	L	L	L	L	H	L	L	L	L	Potato late blight	Phytophthora infestans	Mancozeb
M	H	L	M	M	H	L	L	L	L	Tomato target spot	Corynespora cassiicola	Azoxystrobin
H	M	L	L	M	M	L	L	L	L	Tomato mosaic virus	Tomato mosaic virus	Sulfoxaflor
H	M	L	M	H	L	L	L	L	L	Tomato yellow leaf curl virus	Tomato leaf curl virus	Pyrafluquinazon
H	H	L	L	L	L	L	L	L	L	Tomato bacterial spot	Xanthomonas gardneri	BASF Cabriotop
H	H	L	H	H	L	L	L	L	L	Tomato early blight	Alternaria tomatophila	Bonide Liquid Copper
L	L	M	L	L	H	L	L	L	L	Tomato late blight	Phytophthora infestans	Clutch
H	H	L	H	H	L	L	L	L	L	Tomato leaf mold	Passalora fulva	Spray chlorothalonil
M	H	H	L	L	M	L	L	L	L	Tomato septoria leaf spot	Septoria lycopersici	Copper soap
H	L	L	L	H	L	L	L	L	L	Tomato two spotted spider mite	Tetranychidae	Bifenthrin

*Note: H – High; M – Medium; L – Low

3.3.4 Inference engine and knowledge base

The knowledge base is a component, where knowledge is developed, accumulated, arranged, analyzed, and distributed. It comprises a dataset and a rule base. The dataset gives the requied elements to define the linguistic variables and rules using IF-THEN control constructs. The dataset involves a group of facts utilized to match against the IF (condition) parts of rules accumulated in the knowledge base.

The rule knowledge base follows the Mamdani rule creation. Table 4 shows a few rules derived from the use of Mamdani rule. For an example of pepper bell bacterial spot disease, if the temperature is H && RH is H && RF is L && WS is M && SSH is H && soil moisture is L && pH is L && nitrogen is L && phosphorus is L && potassium is L, then this leaf disease is caused by the pest called Xanthomonas campestris. So, to prevent this pest, the Cuprofix pesticide is recommended.

4. EXPERIMENTAL RESULTS

The performance of the MFL-DCNN-RSF model is assessed by implementing it in Python 3.7.8 using the PVD. Figure 4 shows the application process of MFL-DCNN-RSF. To validate the efficiency of this model, 2250 leaf images with 15 distinct classes are acquired. For the training process, 1500 leaf images (100 images from each class) are collected randomly. For the testing, 750 leaf images (50 images from each class) are collected. Also, the efficiency is analyzed in terms of different metrics. Figure 5 portrays a few samples of the diseased leaf images from each given class.

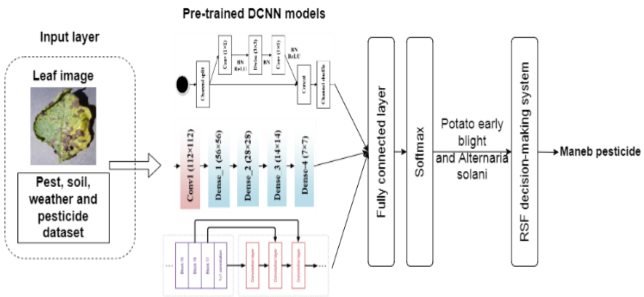

Figure 4. Application process of MFL-DCNN-RSF

Precision is determined by Eq. (8).

$$Precision = \frac{No.of\ exactly\ classified\ diseased\ leaves\ and\ pests}{No.of\ exactly\ classified\ diseased\ leaves\ and\ pests + No.of\ inexactly\ classified\ diseased\ leaves\ and\ pests} \quad (8)$$

Recall is determined by Eq. (9).

$$Recall = \frac{No.of\ exactly\ classified\ diseased\ leaves\ and\ pests}{No.of\ exactly\ classified\ diseased\ leaves\ and\ pests + No.of\ inexactly\ classified\ healthy\ leaves\ and\ pests} \quad (9)$$

F-measure is calculated as Eq. (10).

$$F - measure = 2 \times \frac{Precision \cdot Recall}{Precision + Recall} \quad (10)$$

Accuracy is determined by Eq. (11).

$$Accuracy = \frac{TP + True\ Negative\ (TN)}{TP + TN + FP + FN} \quad (11)$$

The findings of MFL-DCNN-RSF, Tiny-YOLOv3 [24], OSSL [25], and SVM [26] applied on the multi-dimensional dataset (super-resolved leaf disease images, pests associated with the weather, soil factors, and pesticides) are given in Table 5 and the graphical depiction of accuracy ranges is presented in Figure 6.

Figure 6 addresses that the accuracy of the MFL-DCNN-RSF is 10.81% higher than the SVM, 8.07% higher than the OSSL, and 6.19% higher than the tiny-YOLOv3. The precision of the MFL-DCNN-RSF is 10.33% higher than the SVM, 7.41% higher than the OSSL, and 6.01% higher than the tiny-YOLOv3. The recall of the MFL-DCNN-RSF is 12.04% higher than the SVM, 10.17% higher than the OSSL, and 7.41% higher than the tiny-YOLOv3. The comparative scrutiny clarifies that the MFL-DCNN-RSF model guarantees the highest accuracy in classifying the leaf diseases and pests, as well as predicting the suitable pesticides compared to the other models applied to the multi-dimensional dataset. The proposed MFL-DCNN-RSF uses a variety of attributes for pesticide recommendation by classifying leaf diseases and pests, whereas the existing models focus only on the low-resolution leaf and pest images, which may not sufficient to provide maximum accuracy. Also, existing models take more time for learning and have high complexity while increasing the number of data. So, according to the observed accuracies, the MFL-DCNN-RSF model is highly helpful to classify leaf diseases, and pests and recommend suitable pesticides with proper usage for controlling the leaf diseases.

Table 5. Analysis of MFL-DCNN-RSF and existing models for pesticide recommendation

Models	Precision (%)	Recall (%)	F-measure (%)	Accuracy (%)
SVM	89.47	87.19	88.33	89.28
OSSL	91.90	88.67	90.29	91.54
Tiny-YOLOv3	93.11	90.95	92.03	93.16
MFL-DCNN-RSF	**98.71**	**97.69**	**98.20**	**98.93**

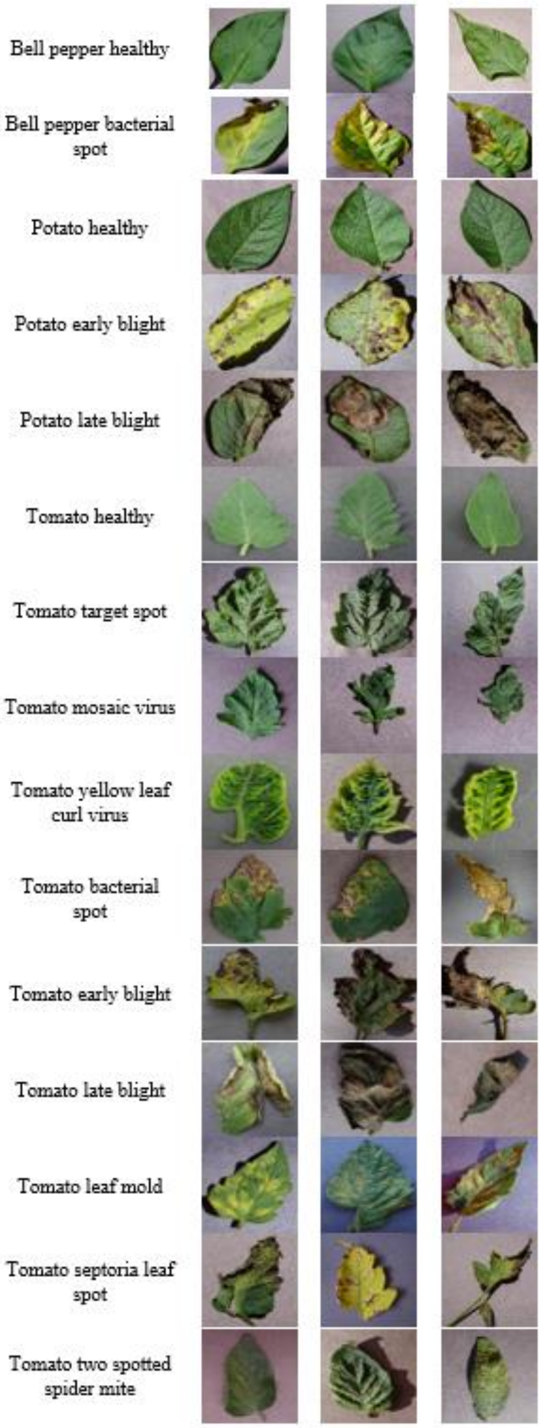

Figure 5. Few sample images of different classes of diseased leaf images

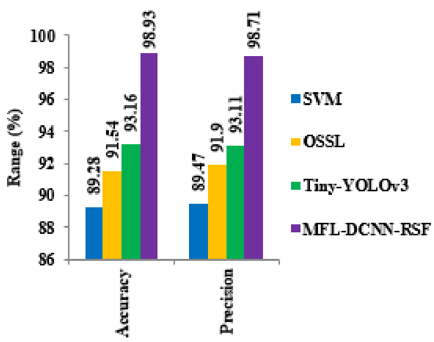

Figure 6. Comparison of proposed and existing pesticide recommendation models

5. CONCLUSIONS

In this article, the MFL-DCNN-RSF model was developed for preventing leaf diseases and pests by recommending suitable pesticides. This model can be helpful for cultivators to use appropriate pesticides for corresponding pests and leaf diseases. As a result, it reduces environmental damages due to the excessive/improper usage of pesticides and enhances crop productivity significantly. The test outcomes proved that the MFL-DCNN-RSF model has a mean accuracy of 98.93%, respectively, contrasted with the other classification models.

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