Chapter 7

CHAPTER 7

PROPOSED MODEL: HYBRID ROUGH SET WITH INTUITIONISTIC FUZZY APPROXIMATION SPACE (RSF)-BASED DECISION SUPPORT SYSTEM FOR PESTICIDE RECOMMENDATION

7.1 INTRODUCTION

Incorrect use of pesticides for the treatment of leaf diseases and the elimination of pests in agricultural settings are discussed in this chapter. Among the numerous pesticide recommendation approaches described, the use of Rough Set (RS) inside an intuitionistic Fuzzy approximation space (RSF)-based decision support system with a Multi-Functional Logistic Neural Network (MFL-DCNN) model is discussed. At the end, it compares the suggested MFL-DCNN-RSF model to other popular models as CNN (Kosamkar et al. 2018), ANFIS (Kuzman et al. 2021), and NE protocol (Amgain et al. 2021).

7.1.1 Techniques Used for Pesticide Recommendation

Different techniques are used for pesticide recommendation. Some of the most common techniques include:

- Pesticide recommendation systems are tools that provide personalized and data-driven suggestions for selecting and applying pesticides to manage pests, and diseases in agricultural and horticultural contexts. These systems leverage various sources of information, including crop characteristics, pest identification, weather conditions, and historical data, to help farmers make informed decisions about pesticide use. However, there are currently no reliable pesticide prescription methods available to farmers. This makes it difficult for them to effectively combat pests and leaf diseases.
- Decision trees: These systems use a decision tree to determine which pesticide is most appropriate (Teng & Savary 1992). The decision tree is a flowchart that branches out based on the pest's characteristics and the crop being grown

- Machine learning: Ip et al. (2018) found that ML may be used to create models that predict which insecticide would be most successful against a given pest. The models are educated using data that details the insect, the crop, and the chemical.
- Rule-based systems: These systems use a set of rules to determine which pesticide is most appropriate for a particular pest. The rules are typically based on the pest's biology, the crop being grown, and the ecological conditions (Debaeke et al. 2009)

7.1.2 Rule-based Decision Support Systems for Pesticide Recommendation

Rule-based pesticide recommendation systems are relatively simple to develop and maintain. An example of a rule-based pesticide recommendation system is given below.

IF pest = "aphid" AND crop = "tomato" THEN recommend pesticide "insecticide A"

IF pest = "fungus" AND crop = "wheat" THEN recommend pesticide "fungicide B"

This rule-based system would recommend insecticide A for aphids on tomatoes and fungicide B for fungi on wheat. Rule-based pesticide recommendation systems can be categorized into different types based on their underlying principles, methods of rule formulation, and complexity. Some common types are given below,

7.1.2.1 Simple Threshold-based Systems

These systems use fixed thresholds for pest population density, weather conditions, or other factors to trigger pesticide recommendations. For example, if pest population exceeds a predefined threshold, a recommendation for pesticide application is provided (Lynn 2019).

7.1.2.2 Expert System-based Systems

Expert systems rely on the knowledge and expertise of agronomists and entomologists to create rule sets. These rules often involve complex conditions and considerations, such as pest life cycles, crop growth stages, and weather interactions (Mansingh et al. 2007).

7.1.2.3 Weather-Driven Systems

These systems primarily base recommendations on weather conditions, as weather significantly influences pest development (Morin et al. 2018). Rules consider parameters like temperature, humidity, rainfall, and wind speed to determine appropriate pesticide actions.

7.1.2.4 Degree-Day Systems

Degree-day systems calculate cumulative heat units (degree-days) to predict the development of pests and diseases. The accumulated degree-days are compared to critical thresholds to suggest the timing of pesticide applications (Chakravarty & Gautam 2004).

7.1.2.5 GIS-Integrated Systems

Geographic Information Systems (GIS) are used to integrate spatial data, such as soil types, topography, and land use, into recommendation systems. GIS-based systems provide location-specific recommendations based on spatial factors (Leh et al. 2013).

7.1.2.6 Integrated Pest Management-IPM Systems

IPM systems consider a holistic approach to pest management by combining multiple strategies, such as biological control, cultural practices, and pesticide use (Baker et al. 2020). Rules consider the hierarchy of interventions to determine the best course of action.

7.1.2.7 Dynamic Systems with Learning

These systems continuously update and refine rules based on user feedback and historical data. ML techniques may be used to adjust rule weights and improve recommendation accuracy over time (Kotsiantis et al. 2006).

7.1.2.8 Sensor-Driven Systems

Sensor-driven systems integrate data from IoT devices and sensors to provide real-time insights on pest populations and environmental conditions. Sensor data enhances the accuracy and responsiveness of recommendations (Mayton et al. 2017).

7.1.2.9 Time-Series Analysis Systems

These systems analyze historical time-series data, such as pest population trends, to make predictions and generate recommendations. Techniques like ARIMA (Auto-Regressive Integrated Moving Average) can be used to model temporal patterns (Khashei et al. 2009).

7.1.2.10 Fuzzy Logic Systems

To deal with ambiguity and imprecision, fuzzy logic systems use linguistic variables and membership functions. Recommendations are made based on the evaluation of fuzzy inputs utilizing rules established using language words (for example, "low," "medium," and "high"). For instance, a system might use fuzzy logic to handle uncertainty while integrating weather data for accurate recommendations (Adriaenssens et al. 2004).

Key components of a fuzzy logic decision systems include:

- Input variables: Identify the relevant input variables that are important for the decision-making process. These variables can include weather factors (Some examples are temperature, humidity, rainfall), soil factors (Some examples are moisture content, nutrient levels), crop-specific parameters (Some examples are growth stage, pest/disease prevalence) and other relevant factors
- Membership functions: Define linguistic terms and design membership functions for each input variable. Membership functions map the input values to their corresponding degrees of membership in the linguistic terms. These functions represent the fuzzy boundaries of the linguistic terms and capture the gradual transition from one term to another
- Rule base: Develop a rule base that represents expert knowledge or decision-making guidelines. The building blocks of a fuzzy rule are an input condition and a subsequent outcome. These rules describe the relationships between the linguistic terms of the input variables and the desired output decisions. The rule base is typically constructed through expert consultations or by analyzing historical data
- Fuzzy inference engine: Apply the fuzzy inference engine to process the input variables and fuzzy rules and determine the appropriate output decisions. The inference engine analyzes the input circumstances to determine the degrees of

truth of the fuzzy rules via the use of fuzzy logic operations including fuzzy AND, fuzzy OR, and fuzzy implication. Aggregation methods, such as max-min or max-product, are often used to combine the outputs of multiple rules

- Output variables and defuzzification: Define the output variables that represent the decisions or actions to be taken based on the fuzzy inference. Assign linguistic terms to the output variables and design corresponding membership functions. The defuzzification process converts the fuzzy output into a crisp output value or decision that can be easily interpreted and implemented
- Model evaluation and refinement: Assess the performance of the fuzzy intelligence decision system using appropriate evaluation metrics and real-world validation data. Refine the membership functions, rule base, or fuzzy inference engine based on the evaluation results to improve the system's accuracy and reliability
- Decision implementation: Utilize the crisp output decisions obtained from the fuzzy intelligence decision system to guide agricultural management practices. These decisions can include irrigation scheduling, pest control measures, fertilization strategies, crop rotation plans, or other actions related to optimizing crop health, resource usage and yield

The following are some of their key advantages:

- Handling uncertainty and imprecision: Fuzzy logic-based approaches are well-suited for managing uncertainty and imprecision inherent in agricultural data. Agricultural systems involve complex and uncertain variables, such as weather conditions, soil properties and crop health. It allows for the representation and processing of imprecise and vague information, enabling decision-making even when data is incomplete or uncertain
- Incorporating expert knowledge: Fuzzy rule-based decision systems can effectively capture and utilize expert knowledge and experience. Agricultural experts possess valuable insights into crop management, pest control and other agricultural practices. Fuzzy systems provide a framework for encoding this knowledge into linguistic rules and membership functions, which can be applied

in decision-making processes. By incorporating expert knowledge, fuzzy systems enhance decision-making abilities and improve the accuracy of agricultural management practices

- Flexibility and adaptability: Fuzzy rule-based decision systems offer flexibility and adaptability to changing agricultural conditions. The linguistic rules and membership functions can be easily modified or updated based on new data or evolving expert knowledge. This adaptability allows the system to respond to variations in crop growth, pest dynamics, climate patterns and other factors affecting agricultural operations

- Transparency and interpretability: Fuzzy logic-based decision systems provide transparency and interpretability. The linguistic terms and fuzzy rules can be understood and interpreted by domain experts and stakeholders, making the decision-making process more transparent. The system's outputs, obtained through defuzzification, can be easily interpreted and explained, aiding in understanding the reasoning behind the decisions. This transparency enhances the stakeholders' trust and acceptance of the decision system

- Integration of diverse variables: Fuzzy logic-based decision systems facilitate the integration of diverse variables in decision-making. Agricultural systems involve a wide range of interconnected factors, such as weather, soil conditions, crop health and management practices. Fuzzy systems can handle multiple input variables with linguistic terms, allowing for a holistic analysis and decision-making process that considers the relationships between these variables

- Optimization and resource efficiency: Fuzzy rule-based decision systems can optimize resource allocation and usage in agriculture. By considering multiple variables and their relationships, fuzzy systems can provide recommendations and decisions that minimize resource waste and maximize resource efficiency. It can be applied to irrigation management, fertilizer application, pest control strategies and other aspects of agricultural management, leading to improved productivity and sustainability

Fuzzy logic-based decision systems in agriculture provide a framework to effectively manage agricultural uncertainties and incorporate expert knowledge into decision-making processes. By considering the imprecise and vague nature of agricultural data, these systems help farmers and stakeholders make more informed and optimized decisions, leading to improved agricultural productivity, resource efficiency and sustainability. However, these decision systems can be less accurate and robust in the pesticide recommendation using multidimensional features. A decision support system is developed using Rough Sets (RS) on intuitionistic Fuzzy approximation Space (RSF) to address this issue and aid in making well-informed judgements on the use of pesticides in agriculture.

A. Rough Set on Intuitionistic Fuzzy Approximation Space-Based Decision Support System

Fuzzification, training, and testing the RSF inference engine are the main responsibilities of this system. Initial steps include defining a fuzzy set, where each element's membership function may have values between (0,1) on a scale from most restrictive to most lenient. As can be seen in Fig. 7.1, fuzzy sets are a generalisation of crisp sets, which only allow for complete or complete non-membership.

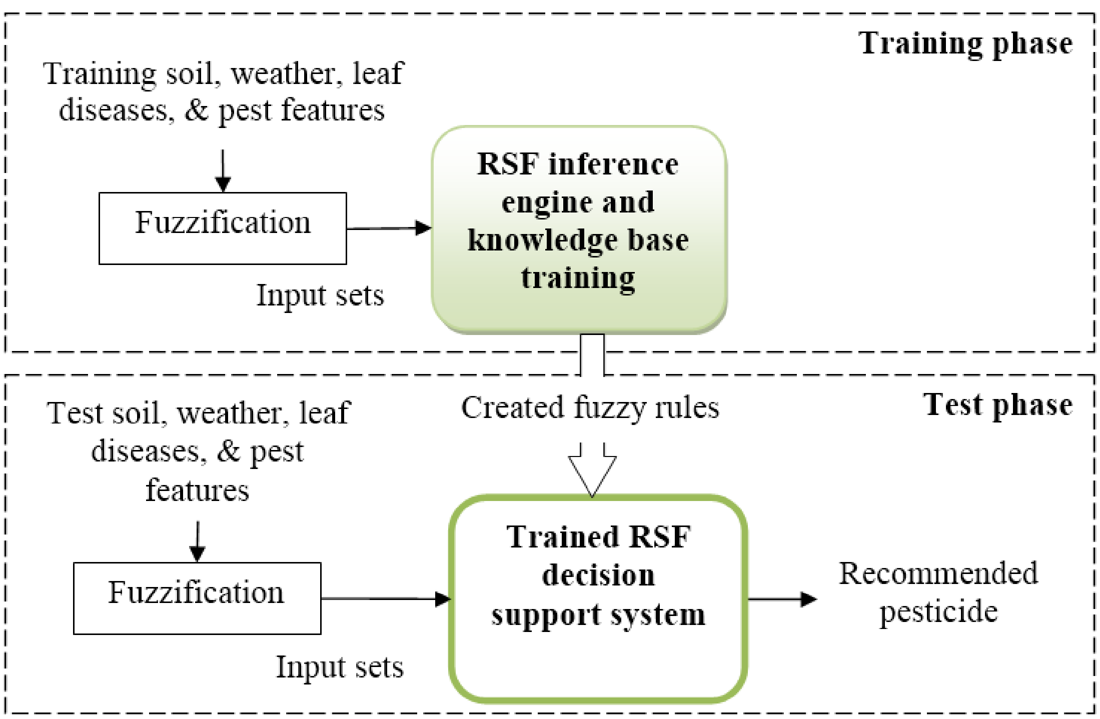

Fig. 7.1 Structure of RSF based Decision Support System

The fuzzy set was generated from the list of multi-dimensional data by

$$X = \{temperature, \ldots, N, P, K,\} \tag{7.1}$$

Each input element is then mapped to a membership value (or membership degree) between 0 and 1 according to a membership function's specifications. Each X element is assigned a membership value between zero and one by the membership function, which is defined as:

$$\mu(x) = \{High, Moderate, Low\} \tag{7.2}$$

(i) RSF System

Consider $U \neq \varphi$ is a quasi finite group of subjects known as space and x is a particular component of U. For each given component X of U, the Intuitionistic Fuzzy Set (ISF) $\{x, \mu_X(x), v_X(x)\}$, where $\mu_X: U \to [0,1]$ and $v_X: U \to [0,1]$ are the levels of membership and non-membership, for all components $x \in U$ such that $0 \leq \mu_X(x) + v_X(x) \leq 1$. The spectrum of uncertainty, which might indicate membership or non-membership, or both, is defined as $\pi_X(x) = 1 - \left(\mu_X(x) + v_X(x)\right)$. Specifically, $\left(\mu_X(x), v_X(x)\right)$ is utilized to define the ISF X. An intuitionistic fuzzy association (IA) on U is an ISF represented on $(U \times U)$ represented using the membership μ_{IA} and the non-membership v_{IA} in.Eq. (7.3).

$$IA = \left\{\left(\mu_{IA}(x_i, x_j), v_{IA}(x_i, x_j)\right) \middle| x_i, x_j \in U\right\} \tag{7.3}$$

Assuming the membership degree $\mu_{IA}(x_i, x_j)$ and the non-membership degree $v_{IA}(x_i, x_j)$ between 2 features x_i and x_j, an IA on U is said to be an intuitionistic fuzzy neighborhood association if and only if it meets the following requirements.

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 $x_i, x_j \in U$.

Take into consideration $J = \{(\alpha, \beta) | \alpha, \beta \in [0,1]\}$ and $0 \leq \alpha + \beta \leq 1$. After, for any $(\alpha, \beta) \in J$, (α, β)-cut is offer as $IA_{\alpha,\beta} = \left\{(x_i, x_j) \middle| \mu_{IA}(x_i, x_j) \geq \alpha \; and \; v_{IA}(x_i, x_j) \leq \beta\right\}$.

It has been noticed that the two characteristics 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 characteristics Matching to IA with values of x_i and x_j is referred to as (α, β), Whenever there exists a set of components $u_1, u_2, \ldots, u_n$ 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 case, x_i is shown to be a uniformity association $IA_{(\alpha,\beta)}$. A component x in U has uniformity class $IA_{(\alpha,\beta)}$ if and only if $[x]_{(\alpha,\beta)}$. In this context, "IF approximation space" refers to the pair $= (U, IA(\alpha, \beta))$.

Imagine $X \subseteq U$. As a result, Eqns. (7.4) & (7.5) define the minimum and maximum (α, β) approximation of X in the generalized approximation space $K = (U, IA(\alpha, \beta))$ as $\left(X_{Min}^{\alpha,\beta}, X_{Max}^{\alpha,\beta}\right)$ respectively.

$$X_{Min}^{\alpha,\beta} = \cup \left\{Y \middle| Y \in IA_{\alpha,\beta}^{*} \; and \; Y \subseteq X\right\} \tag{7.4}$$

$$X_{Max}^{\alpha,\beta} = \cup \left\{Y \middle| Y \in IA_{\alpha,\beta}^{*} \; and \; Y \cap X \neq \varphi\right\} \tag{7.5}$$

A When $X_{Max}^{\alpha,\beta} \neq X_{Min}^{\alpha,\beta}$ a set X is said to be (,)-rough. Similarly, a set X is said to be (α, β)-crisp if and only if $X_{Max}^{\alpha,\beta} = X_{Min}^{\alpha,\beta}$. A set X is said to be (α, β)-rough if and only if the limit $LIM_{IA}^{\alpha,\beta} = X_{Max}^{\alpha,\beta} - X_{Min}^{\alpha,\beta}$ such that $LIM_{IA}^{\alpha,\beta} \neq \varphi$.

(ii) Fuzzification

To achieve this goal, this method use the membership function provided by the fuzzy knowledge base to convert a granular input into a linguistic variable. Due to the fact that linguistic variables are represented as three distinct groups—low (L), medium (M), and high (H)—the triangle membership function is put to use. The method cannot function without input from the user. Significant parameters for selecting the most effective pesticide include compositional ranges across many dimensions. As shown in Table 7.1, such n-dimensional data is organized into three linguistic variables with values between 0 and 1.

Table 7.1 RSF-based Decision Input Variables for Weather and Soil Attributes

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

(iii) Determination of Membership and Non-Membership Functions

The greatest degree of indiscernibility across all characteristics is determined by the intuitionistic fuzzy tolerance. The RSF produces (α, β) uniformity classes, α with denoting a degree of membership and β denoting a degree of non-membership. Better predictions of effective pesticides can be made when the degree of membership is high and the degree of non-membership is low.

If the value of belonging is 1, and the value of not belonging is 0 then, the model cannot interpret the data since each forecast may correctly contain a specific pesticide. The reason for this is because the feature values are quantitative in nature. The ranges of both the membership and non-membership associations are calculated such that the total falls inside the interval [0,1].

In this case, pesticide forecasting takes into account factors such as leaf diseases, pests, soil, and climate. Changing the values of α and β may cause a separation between these characteristics. As the range of α is decreased and the range of β is increased, gradually the number of features will become more essential. Eqns. (7.6) & (7.7) explain the membership degree (μ) and the non-membership degree (v) between x_i and x_j, respectively:

$$\mu_A(x_i, x_j) = 1 - \frac{\left|V_{a_i}^{x_i} - V_{a_i}^{x_j}\right|}{\max\left(V_{a_i}\right)} \tag{7.6}$$

$$v_A(x_i, x_j) = 1 - \frac{\left|V_{a_i}^{x_i} - V_{a_i}^{x_j}\right|}{2 \times \max\left(V_{a_i}\right)} \tag{7.7}$$

In Eqns. (7.6) & (7.7), $V_{a_i}^{x_i}$ denotes the value of x_i for a particular crop a_i.

(iv) Inference Engine and Knowledge Base

Developing, collecting, organizing, analyzing, and disseminating information are all functions of the knowledge base. A dataset plus a set of guidelines make up this. The data collection supplies the building blocks for establishing language variables and rules using IF-THEN decision-making structures. The dataset may be used to validate the IF (condition) parts of the rules in the knowledge base. Rule knowledge base in line with Mamdani rule generation may be used to anticipate the most effective pesticide for a specific leaf disease and insect.

7.2 BUILDING THE PROPOSED MODEL

In order to provide educated pesticide recommendations, the MFL-DCNN classifier is used to detect leaf diseases and pests. The model is an Intuitionistic Fuzzy Approximation and was constructed using Rough Set. The Plant Village Dataset (PVD), soil, weather, pest and pesticide datasets provided in Chapter 3 is utilized for the experiments. The stages engaged in the proposed MFL-DCNN-RSF are shown in Fig 7.2, wherein dataset preparation is given in Chapter 4, and the high-resolution leaf disease image generation is presented in Chapter 5. Also, the third stage of classifying leaf diseases and pests is given in Chapter 6. The final stage such as the pesticide recommendation is performed using the proposed RSF-based decision support system.

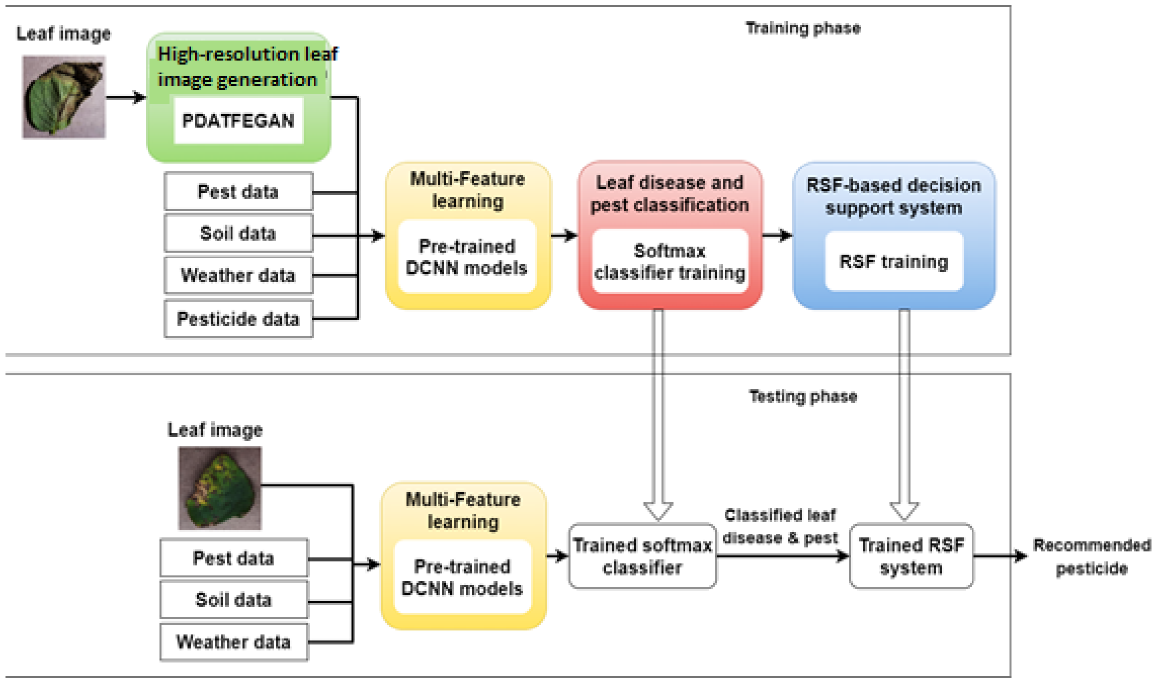

Fig. 7.2 Block Diagram of the Proposed MFL-DCNN-RSF Model

7.2.1 Pesticide Recommendation using RSF-based Decision Support System

Steps from section 7.1.2.10 of the RSF decision support system are followed to determine which pesticides should be used once the MFL-DCNN classifier has been used to categorize leaf diseases and pests. Several examples of pesticides used to treat leaf diseases are shown in Table 7.2, along with the insects, soil, and climate that are linked to these illnesses.

Table 7.2 Types of Pesticides Used for Different Leaf Diseases

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

Leaf Disease Name	Pest Name	Soil & weather factors	Pesticide Name
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

In this research, the RSF is trained to create rules, as given in Table 7.3, based on the multi-dimensional features for pesticide recommendation. The pest Xanthomonas campestris is to blame for bacterial spot disease in pepper bells if the following circumstances are met: (a) temperature is H, (b) relative humidity is H, (c) rainfall is L, (d) wind speed is M, (e) soil moisture is L, (f) pH is L, (g) nitrogen is L, (h) phosphorus is L, and (g) potassium is L. Therefore, the Cuprofix insecticide is suggested for protection against this nuisance.

Table 7.3 Rules of RSF System 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

Temperature	RH	RF	WS	SSH	Soil moisture	pH	N	P	K	Leaf diseases	Pests	Pesticide
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

7.3 RESULTS AND DISCUSSION

The metrics used to evaluate the proposed MFL-DCNN-RSF model's performance in comparison to the baseline models are shown below. Chapter 3 describes the datasets, metrics, and system settings used for assessment. Table 7.4 displays the precision, recall, f-measure, and accuracy values obtained from testing the MFL-DCNN-RSF model on the multi-dimensional datasets.

Table 7.4 Comparison of proposed MFL-DCNN-RSF Model

Performance Evaluation Metrics	CNN	NE Protocol	ANFIS	MFL-DCNN-RSF
Precision	0.8875	0.9048	0.9313	0.9871
Recall	0.8901	0.9095	0.9542	0.9769
F-measure	0.8888	0.9072	0.9428	0.9820
Accuracy	88.95%	90.99%	95.31%	98.93%

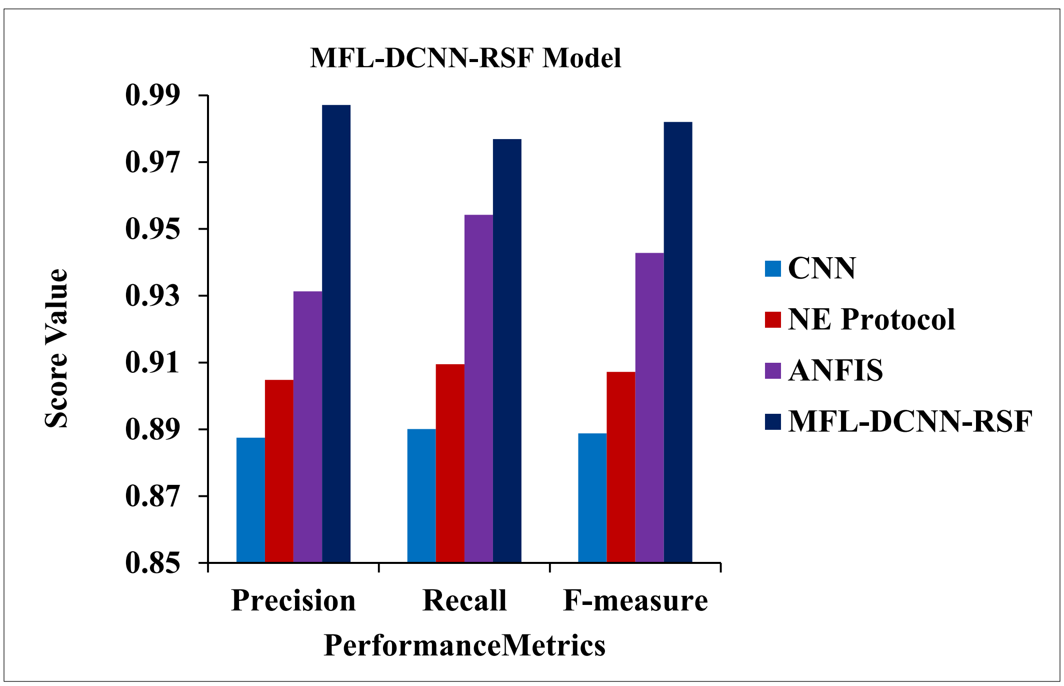

Fig. 7.3 Results of Proposed MFL-DCNN-RSF Model

Fig. 7.3 depicts a comparison of the proposed MFL-DCNN-RSF to other pesticide recommendation models evaluated on the same multi-dimensional dataset in terms of accuracy, recall, and f-measure. It is observed that the MFL-DCNN-RSF improves accuracy over the CNN, NE protocol, and ANFIS models by 11.22%, 9.1%, and 5.99%, respectively. When compared to the CNN and NE protocol models and the ANFIS model, the MFL-DCNN-RSF's recall is 9.75%, 7.41%, and 2.38% higher, respectively. The f-measure value of the MFL-DCNN-RSF is increased by 10.49%, 8.25% and 4.16% compared to the CNN, NE protocol and ANFIS models, respectively. This suggests that the MFL-DCNN-RSF is superior to other agricultural recommendation models in terms of increasing crop production via pesticide recommendations.

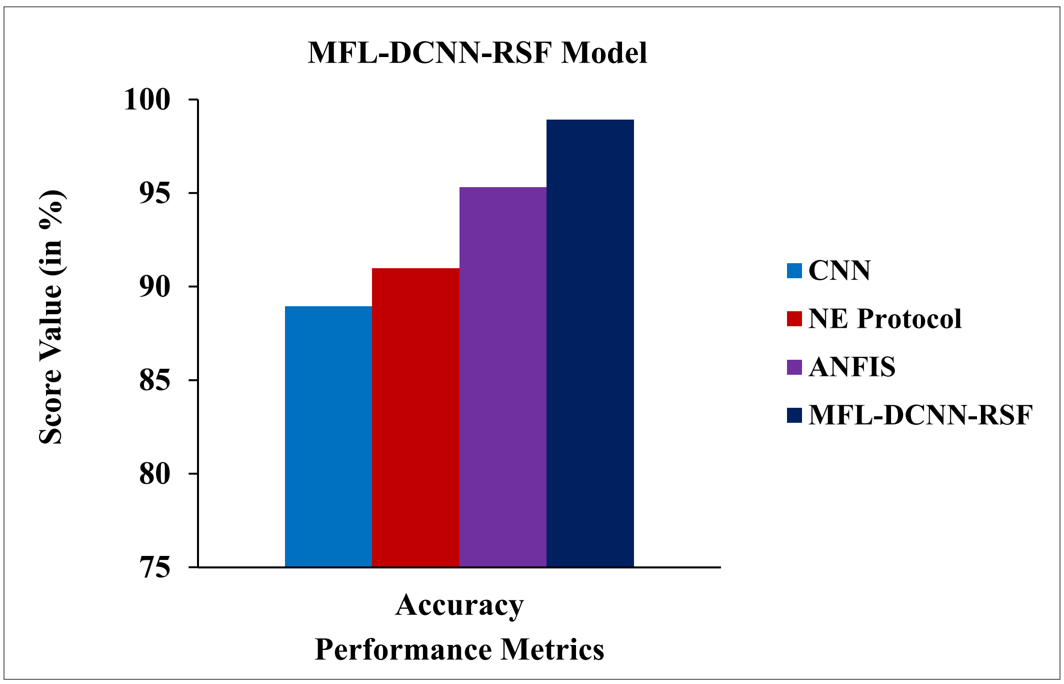

Fig. 7.4 Accuracy Comparison of MFL-DCNN-RSF Model

In terms of the accuracy of various pesticide recommendation models tested on the considered multi-dimensional dataset as shown in Fig 7.4. Noted improvements in accuracy of 11.22%, 8.73%, and 3.8% over the CNN, NE protocol, and ANFIS models, respectively, are achieved by the MFL-DCNN-RSF. This is achieved because of using Intuitionistic fuzzy RSs to build a flexible and robust decision support system that handles the inherent uncertainty and vagueness in agricultural data.

7.4 SUMMARY

To summarize, this chapter presented the overview of rule-based decision support systems for agricultural applications. The RSF-based decision support system for pesticide recommendation is also discussed. For various classes of leaf diseases, pests, and pesticides, the performance of the models is analysed. Insecticide recommendations and disease classification for leaf crops using the proposed MFL-DCNN-RSF model are discussed.