Chapter 6

CHAPTER 6

PROPOSED MODEL: A MULTI-DIMENSIONAL FEATURE LEARNING-BASED DCNN (MFL-DCNN) FOR LEAF DISEASE AND PEST CLASSIFICATION

6.1 INTRODUCTION

This chapter presents an overview of challenges in leaf disease and pest classification. It also discusses the role of ensemble learning using the pre-trained DCNN models to handle multi-dimensional features for both leaf disease and pest classification. Finally, many state-of-the-art models are compared to the Multi-Dimensional Feature Learning-based DCNN (MFL-DCNN) model utilising a wide range of metrics. These include PestNet (Liu et al. 2019), multi-scale CNN (Li et al. 2019), ResNet34* (Alves et al. 2020), OSSL (Rustia et al. 2021), and YOLOv.

6.2 SIGNIFICANCE OF PEST CLASSIFICATION IN LEAF DISEASE DETECTION

The issue with categorising leaf diseases is that they are often brought on by a wide range of hazardous pests. Term "pest" is used to identify a genus or species of animal that causes significant monetary loss to farmers by consuming plant tissue used in agricultural production. The majority of pests are insects or mites. Pest proliferation is determined by the local climate, exogenous pest population and harvest control strategies. The presence of pests and illnesses not only poses a risk to the farmer but also to nearby and remote farms. Therefore, it is essential to use a wide variety of characteristics, including photos of leaf illnesses, soil conditions, weather patterns, etc., to categorize both leaf diseases and the pests that cause them. These spatial aspects might be confusing and convoluted. This can make it difficult to develop a classifier that can accurately identify the different features and their relationships. Pest classification is crucial when combined with leaf disease detection for various significant reasons:

- Comprehensive crop health assessment: Integrating pest classification with leaf disease detection enables a comprehensive assessment of crop health. This approach allows for the identification of both biotic factors (such as diseases and pests) and abiotic factors (including environmental stress and nutrient deficiency) that affect plant health. Acquiring a holistic understanding of these factors is essential for effective crop management.

- Early detection of multiple threats: Early detection of illnesses and pests is essential for effective and timely management. Many pests and diseases often exhibit subtle initial symptoms, which can be mistakenly attributed to other issues. By monitoring both simultaneously, farmers can promptly implement necessary measures to prevent or minimize damage to their crops.
- Pesticide optimization: It is essential to have a comprehensive understanding of different pest types to ensure the efficient application of pesticides. This knowledge enables the precise use of specific chemical treatments, thereby minimizing the requirement for indiscriminate pesticide usage. Such an approach not only reduces the adverse effects on the environment but also prevents potential economic consequences.
- Data-driven decision making: In order to effectively control diseases and pests, farmers and agricultural specialists need access to data on both. This data helps determine the most effective management practices, intervention timing, and control strategies for diseases and pests.
- Environmental and economic sustainability: Promoting the adoption of sustainable pest management strategies, such as minimizing pesticide usage, is not only advantageous for the environment but also economically feasible. By reducing unnecessary pesticide applications, farmers can save on expenses and greatly mitigate the adverse environmental effects linked to farming.

Combining pest classification with leaf disease detection offers a more comprehensive and efficient approach to managing crop health, thereby ensuring sustainable and productive agriculture.

6.2.1 Agricultural Crop Pests

India's agriculture plays a crucial role in socioeconomic development, boasting a vast and diverse system. The country takes pride in having the world's largest research system, with over one lakh people engaged in research and 27,500 scientists (Herrera et al. 2021). As the global population is projected to double by 2050, food production has already increased by 70% (Ranganathan et al. 2018). Nevertheless, the sector faces challenges such as food safety, water contamination, and climate change, which have put strain on its operations and contributed to 20% of anthropogenic greenhouse gas emissions (Fan et al. 2021).

Pests are living organisms that can cause harm to the environment or spread pathogens, making them undesirable. They can take the form of parasites, diseases, or destructive organisms. While pests can be beneficial or controlled in certain environments, they can be harmful in others. Pests and other creatures may drastically reduce agricultural yields, therefore taking preventative measures is crucial. Pests can include insects, weeds, diseases, species, or microbes. Examples of pests that affect plants are presented in Fig. 6.1.

Fig. 6.1 Different Pests that affect Plants

Aphids, red-white creepy crawly vermin, scale, mealybugs, thrips, whiteflies, and various soil-dwelling insects are commonly encountered pests (Daughtrey and Buitenhuis 2020). If the problem is detected early, it is usually addressed without the need for insecticides, which is by far the best option. The most common plant pest insects are shown in Fig. 6.2.

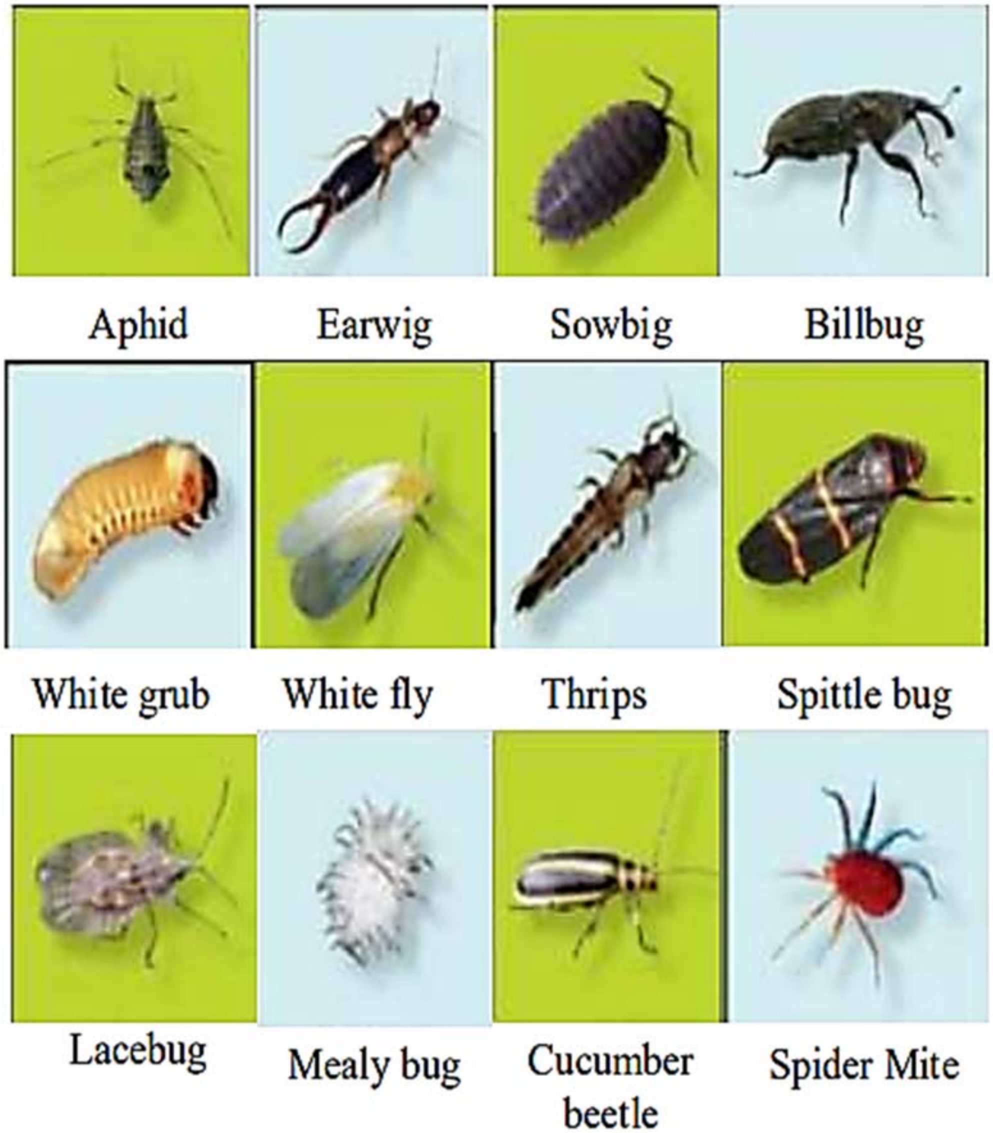

Fig. 6.2 Plant Pest Insects

- **Aphids**

Aphids are common insects found in houseplants, but they can be easily controlled. These pests feed on the plant's sap, causing damage to new growth. Aphids come in different colors and can be identified on the undersides of leaves, usually in groups. Heavy infestations result in the plants being covered in sticky honeydew. If there are female aphids present in a residence, they will take care of any infestation (Singh and Singh 2021). Also, Diazinon, Malathion and systemic pesticides can be used to control aphids. A visual representation of aphids is presented in Fig. 6.3.

Fig. 6.3 Aphids

- **Spider Mites**

These are almost impossible to notice with the naked eye. They are extremely small, and will likely need a magnifying lens to find them. They typically affect newly formed leaves and small flowers. Infested plants will lose their green color and appear bronzed. In severe cases, the bugs will create a smooth webbing to cover the undersides of the leaves. Controlling a plant that has been infested with these parasites will be challenging, if not impossible. Tollerup and Higbee (2020) recommend getting rid of the plant as soon as possible and cleaning it with an insecticidal cleaner once a week. Systemic insect sprays are effective if used at the right time during an infestation. Fig. 6.4 is a diagram depicting spider mites.

Fig. 6.4 Spider Mites

- **Mealy Bugs**

Mealybugs are small insects that have a resemblance to white tufts of cotton. They can typically be found on the underside of leaves and at the top of leaf joins on stems. These bugs are most active during dry and warm weather conditions. Some species of mealybugs hide in the soil, and their white, waxy skin protects them from rain (Subramanian et al. 2021). They are commonly found in citrus and tropical trees and can grow up to a length of 3mm. A visual illustration of Mealy Bugs is given in Fig. 6.5. Worldwide, a total of 158 species have been identified as pests.

Fig. 6.5 Mealy Bugs

• **Whiteflies**

The adult whitefly is a small, white insect. Their evasive behavior when attempt to remove them from plants makes controlling them challenging. The immature stage of the whitefly resembles scales and does not move, so it is during this phase that should eliminate them by washing or immersing them in insecticidal cleaner every week (Manzari and Fathipour 2021). Pesticides and diazinon droplets are highly potent. A visual illustration of whiteflies is provided in Fig. 6.6.

Fig. 6.6 Whiteflies

• **Scale Insects**

Scale insects often multiply in large numbers because they often go unnoticed. They have an oval-shaped structure, measuring 3mm in length, and resemble small chestnut limpets. The hard shell of these insects protects them from insecticides, making them more difficult to eliminate. Scales are typically found on stems and the undersides of leaves, although some species can be found on the upper surface of leaves. Additionally, the presence of harmful fungi can cause leaves to turn yellow (Normark et al. 2019). In the case of lightly affected house plants, these insects can be removed using soft brushes and cotton scrub dipped in soapy water. The appearance of scale insects is illustrated in Fig. 6.7.

Fig. 6.7 Scale Insects

• **Soil Insects**

When these insects come to land after watering, they can be observed. Some adult insects and hatchlings may fly or crawl on the dirty region. They usually do not cause significant harm to the plants (Nyamwasa etal. 2018). However, if there are large populations, they might cause shrinkage and hinder plant development due to minimal root trimming. Fortunately, spraying insecticidal cleanser on the dirt will usually solve the problem. In general, systemic bug sprays are effective in controlling these insects. The presence of soil insects is illustrated in Fig. 6.8.

Fig. 6.8 Soil Insects

- **Ants**

The harm caused by ants is generally unintended and is influenced by the mealy bugs and aphids that they "ranch" for honeydew. However, as ants tunnel to build their nests, they may inadvertently damage the plant's root system (Parr and Bishop 2022). In most cases, the problem can be resolved by soaking the affected area with bug sprays or cleansers.

Effective options include Malathion, diazinon, and systemic bug sprays. A visual representation of ants is given in Fig. 6.9.

Fig. 6.9 Ants

- **Thrips**

Thrips are small and difficult to detect. These insects are light chestnut and have a slender body. When fully grown, they tend to migrate to different crops when disturbed. Thrips cause harm and scarring to plants by "scratching" through the leaves to get to the plant fluids they feed on. In most cases, the problem may be solved by cleaning the area using an insecticidal cleanser. Pesticides such as diazinon and Malathion is commonly used to control these insects. However, systemic insect sprays are not often successful in managing thrips (Mound et al. 2022). A visual illustration of Thrips is shown in Fig. 6.10.

Fig. 6.10 Thrips

- **Earwigs**

Earwigs are a common insect found in Iowa, often discovered under or inside leaves. They occasionally enter ear canals by mistake to lay eggs. These bugs are not always abundant and are only spotted occasionally, typically after a year or more in a moist climate. Earwigs have a distinctive bent shape and resemble calipers, while females are straight and can be used as both a hostile and defensive weapon (Meunier 2023).

They measure about 5/8 inch in length and have a dull chocolate color, with a rose head and pale yellow-chestnut legs. Outdoor creatures and earwigs feed on damp, decaying plant material and can be found in various locations such as logs, beneath mulch, piles of kindling, dead leaves, garbage, and damaged wood. Although they do attack living plants, earwigs are considered minor plant pests in Iowa. A visual illustration of earwigs is provided in Fig. 6.11.

Fig. 6.11 Earwigs

• **Caterpillars**

Caterpillar is a commonly used term for individuals belonging to the order Lepidoptera. However, the use of this word is subjective, as with most other names. It is worth noting that sawfly hatchlings are often referred to as caterpillars. Most caterpillars are herbivorous and primarily consume plants. They are generally aggressive eaters, and a significant percentage of them are considered pests in rural areas (Blažek et al. 2021). Many moth species are primarily known for their caterpillar stage due to the damage they cause to agricultural produce, while the moths themselves are typically dark in color.

On the other hand, certain types of caterpillars are highly valued for their silk production, as a source of nutrition for humans or animals, or organic pest control purposes. The structure of various caterpillars is illustrated in Fig. 6.12.

Fig. 6.12 Caterpillars

• **Grasshoppers**

Grasshoppers are medium-sized insects that inhabit a wide range of habitats. They typically measure between 1 and 7 cm in length when fully mature. These insects possess attacking mouth parts, two types of wings, and long hind legs that enable them to hop. Additionally, they have small antennae and large eyes, blending seamlessly with their surroundings through a combination of cocoa, green, and muted hues. Male grasshoppers exhibit vibrant colors on their wings to attract mates of the opposite sex (Olfert et al. 2021). Some species of grasshoppers consume poisonous plants and store the toxins within their bodies as a defense mechanism. These particular grasshoppers display bright colors as a warning to predators that they are unpalatable. Their abdomens are rounded with a curved shape, while females possess a more symmetrical form. A visual illustration of grasshoppers is given in Fig. 6.13.

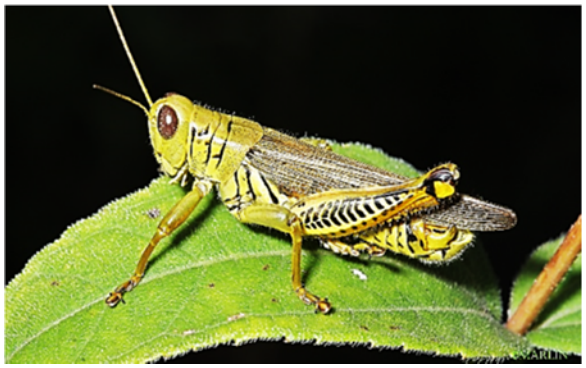

Fig. 6.13 Grasshoppers

6.2.2 Considerations for Soil, Weather and Pest Data in Leaf Disease and Pest Classification

To accurately classify leaf diseases and pests, it is essential to consider various factors related to soil, weather, and pest data. For accurate categorization of leaf diseases and pests in precision agriculture, it is essential to analyze soil composition, meteorological factors, and pest data. These factors are closely connected to crop health and directly impact the occurrence and severity of pest and disease outbreaks. A plant's susceptibility to diseases and pests is influenced by its capacity to absorb nutrients from the soil and by its overall resilience. Furthermore, climatic factors including temperature, humidity, and precipitation significantly affect the frequency and intensity of infectious diseases and insect infestations. These conditions create favorable environments for their growth and development. Furthermore, having comprehensive pest data is vital in distinguishing between disease symptoms and pest damage. By incorporating these environmental and biological factors, classification models can provide informed and contextually relevant predictions. This enables farmers to implement targeted and sustainable management strategies that enhance crop health and optimize agricultural yields.

6.3 Overview of Multi-Dimensional Features Learning

The problem associated with the leaf disease classification is that typically leaf diseases are caused by a variety of harmful pests. Pests are a class of creatures that, when they feast on agricultural plants, may cause significant monetary losses. The majority of pests are insects or mites. Pest proliferation is determined by the local climate, exogenous pest population and harvest control strategies. The presence of pests and illnesses not only poses a risk to the farmer but also to nearby and remote farms. Therefore, it is essential to use a wide variety of characteristics, including photos of leaf illnesses, soil conditions, weather patterns, etc., to categorize both leaf diseases and the pests that cause them. These spatial aspects might be confusing and convoluted. This can make it difficult to develop a classifier that can accurately identify the different features and their relationships. There are a number of techniques that can be used to handle multi-dimensional features in leaf disease and pest classification. Some of the most common techniques include:

- Dimensionality reduction: The term refers to the method used to reduce a dataset's feature count. PCA (Ringnér 2008), t-distributed Stochastic Neighbor Embedding (t-SNE; Soni et al. 2020), and auto-encoders (San Martin et al. 2019) are only few of the approaches that may be used for this purpose. These methods can reduce the complexity of the problem, which can make it easier to train a classifier and improve the interpretability of the classifier. But they can lose information during the dimensionality reduction task.
- Feature selection: It's the method of narrowing down characteristics to those that are most important for making a classification (Dash & Liu, 1997). This can be done using a variety of methods, such as statistical methods, ML methods, or expert knowledge. These techniques may lessen the problem's complexity while increasing the classifier's accuracy. But these models can be time-consuming and computationally expensive.
- Deep learning: In order to deal with multi-dimensional characteristics, DL models may learn them from data (Elboushaki et al., 2020). These models can learn complex features from data, which can lead to better classification accuracy. However, they can be time-consuming and computationally expensive to train. Also, they can be difficult to interpret the results.

- Ensemble learning: It is the process of combining the predictions of multiple classifiers (Sagi & Rokach 2018). Combining multiple classifiers or models that specialize in different aspects of the multi-dimensional data can improve classification accuracy. These models can be more robust to noise and outliers than a single classifier.

Compared to all techniques, ensemble learning can be promising technique that can used to enhance the accuracy of classifying multi-dimensional features in many applications like crop disease diagnosis, yield prediction and soil classification.

6.3.1 Benefits of Using Ensemble Learning

The goal of ensemble learning is to enhance prediction performance and generalization by merging many individual models (Barandela et al., 2003). When dealing with complicated and noisy multi-dimensional data, as is often the case in the context of leaf disease and pest classification, ensemble approaches may improve the accuracy and resilience of classification models. Some applications of ensemble learning in leaf disease and pest classification include:

- Improved classification accuracy: Ensembles combine predictions from multiple base models, which often leads to more accurate classifications. When dealing with diverse and noisy data from different sources, ensembles can capture a broader range of patterns and features.
- Reduced overfitting: Ensembles are less prone to overfitting compared to individual models, especially when the dataset is limited or noisy. By combining multiple models, ensembles mitigate the risk of learning noise.
- Handling class imbalance: Class imbalance is common in leaf disease and pest classification tasks. Ensembles can help by ensuring that the minority classes receive more attention through weighted voting or boosting techniques.
- Model robustness: Ensembles are less sensitive to small perturbations in the data, which can result from variations in lighting, weather conditions, or different leaf orientations. Robustness is especially important in outdoor environments where lighting and weather conditions can vary significantly.

- Capturing diverse features: Different base models in an ensemble may excel at capturing different types of features or patterns in the data. Combining these models allows the ensemble to leverage the strengths of each individual model, resulting in better overall feature representation.
- Model diversity: Ensuring diversity among base models in an ensemble is important. Models trained with different algorithms, architectures, or features are more likely to capture distinct patterns.

6.3.1.1 Multi-dimensional Feature Learning Ensemble Classifier

The advantages mentioned above inspired the development of an ensemble classification model that makes use of several pre-trained DCNN models for MFL, including ShuffleNetV2, DenseNet121, and MobileNetV2. For pest and disease classification in leaves, these DCNN results are translated to the FC layer, then passed on to a softmax classifier. Section 4.3.2 displays all of the available pre-trained DCNN models. Fig. 6.1 depicts the architecture of the MFL ensemble DCNN classifier, which makes use of multidimensional features (such as high-resolution leaf images, pest data, meteorological data, and soil data).

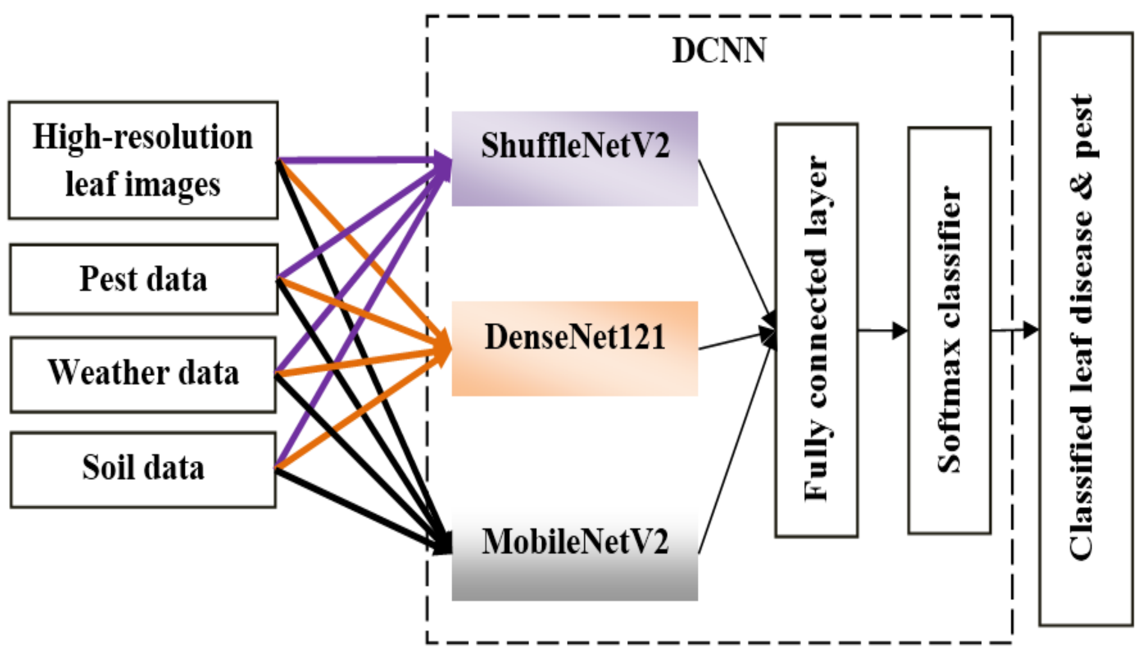

Fig. 6.14 Structure of MFL Ensemble DCNN Classifier

6.4 BUILDING THE PROPOSED MODEL

The MFL-DCNN classifier model is developed as a solution to the learning multi-dimensional features for leaf disease and pest classification. The model has been built by ensemble the ShuffleNetV2, DenseNet121 and MobileNetV2 models. The Plant Village Dataset (PVD), soil, weather and pest datasets provided in Chapter 3 is utilized for the experiments. The stages engaged in the proposed MFL-DCNN are shown in Fig 6.2, wherein dataset preparation is given in Chapter 4, and the high-resolution leaf disease image generation is presented in Chapter 5. The final stage such as the leaf disease classification is performed using the proposed MFL-DCNN classifier.

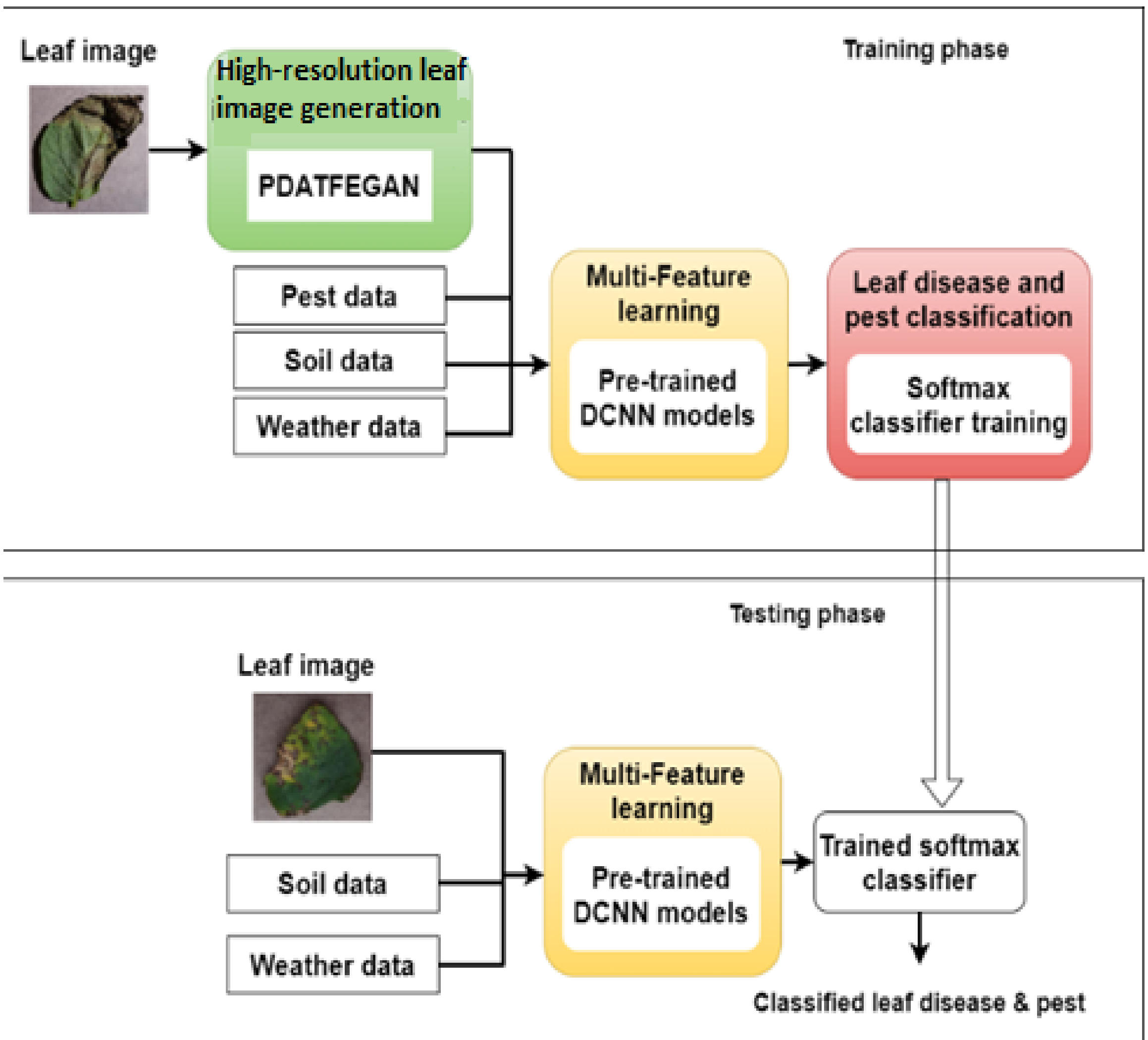

Fig. 6.15 Block Diagram of Proposed MFL-DCNN Model

6.4.1 Training and Testing MFL-DCNN Model

The MFL-DCNN classifier is executed for both leaf disease and pest classification after the datasets of high-resolution leaf disease pictures, pests, soil, and weather are gathered, as described in section 6.3.1.1. In this research, ensemble classifier is adopted rather than using independent pre-trained DCNN classifiers for learning multi-dimensional features. In the MFL-DCNN model, the network is built and trained using the parameters given in Table 4.5 with training images.

The trained model is then applied to the test dataset, where it classifies the leaf diseases and pests. Table 6.1 displays the findings of the classification of pests responsible for leaf diseases.

Table 6.1 Classified Leaf Diseases and Related Pests

Leaf diseases	Pest
Pepper bell bacterial spot	Xanthomonas campestrics
Potato Early blight	Alternaria solani
Potato late blight	Phytophthora infestans
Tomato target spot	Corynespora cassilicola
Tomato mosaic virus	Tomato mosaic virus
Tomato yellow leaf curl virus	Tomato leaf curl virus
Tomato bacterial spot	Xanthomonas gardneri
Tomato early blight	Alternaria tomatophila
Tomato late blight	Phytophthora infestans
Tomato leaf mold	Passalora fulva
Tomato septoria leaf spot	Septoria lycopersici
Tomato two spotted spider mite	Tetranychidae

6.5 RESULTS AND DISCUSSION

Below are the metrics utilised to compare the performance of the proposed MFL-DCNN model to that of the baseline models. Chapter 3 explains the datasets, assessment measures, and system settings in depth. Table 6.2 shows the precision, recall, f-measure, and accuracy results for the MFL-DCNN model when it was evaluated on the multi-dimensional datasets.

Table 6.2 Comparison of Proposed MFL-DCNN Model

Performance Evaluation Metrics	PestNet	Multi-scale CNN	ResNet34*	OSSL	YOLOv5-GhostNet	MFL-DCNN
Precision	0.8651	0.8719	0.8804	0.8972	0.9425	0.9649
Recall	0.8688	0.8745	0.8811	0.8928	0.9283	0.9512
F-measure	0.8670	0.8732	0.8808	0.8950	0.9354	0.9581
Accuracy	86.85%	87.24%	88.16%	89.92%	94.31%	96.57%

Using the examined multi-dimensional dataset for leaf disease and pest classification, the suggested MFL-DCNN model was compared to other classifiers using precision, recall, and f-measure (Fig. 6.3). Results show that MFL-DCNN outperforms PestNet, multi-scale CNN, ResNet34*, OSSL, and YOLOv5-GhostNet models in terms of precision by 11.5%, 10.7%, 9.6%, 7.5%, and 2.4%, respectively. The recall of the MFL-DCNN is enhanced up to 9.5%, 8.8%, 8%, 6.5% and 2.5% compared to the PestNet, multi-scale CNN, ResNet34*, OSSL and YOLOv5-GhostNet models, respectively. The f-measure of the MFL-DCNN is maximized up to 10.5%, 9.7%, 8.8%, 7.1% and 2.4% compared to the PestNet, multi-scale CNN, ResNet34*, OSSL and YOLOv5-GhostNet models, respectively.

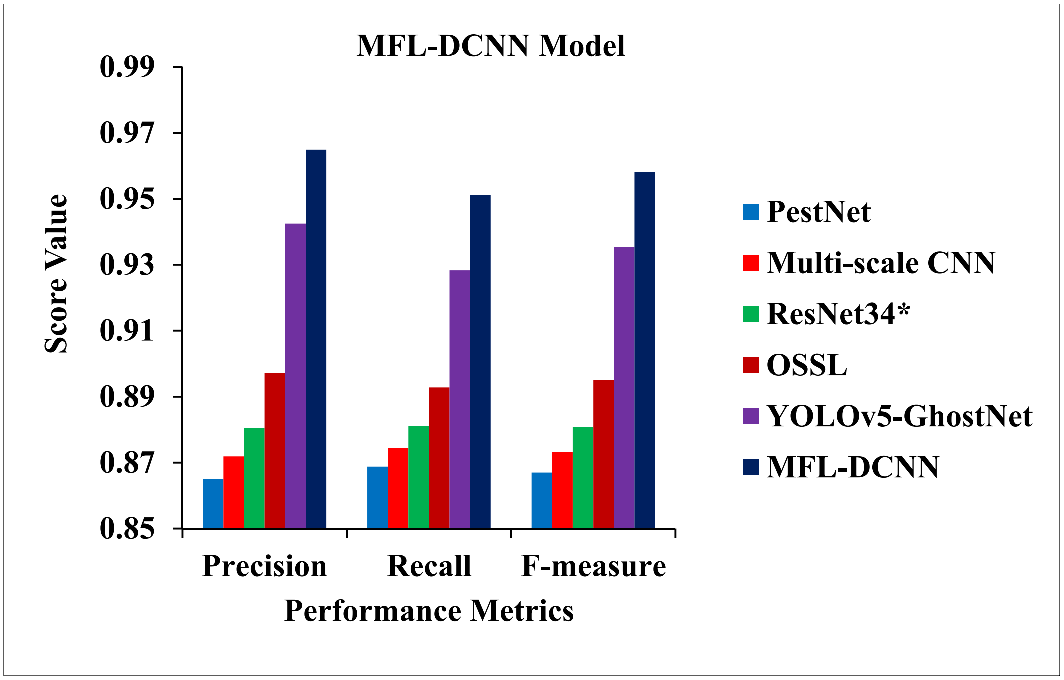

Fig. 6.16 Result of Proposed MFL-DCNN Model

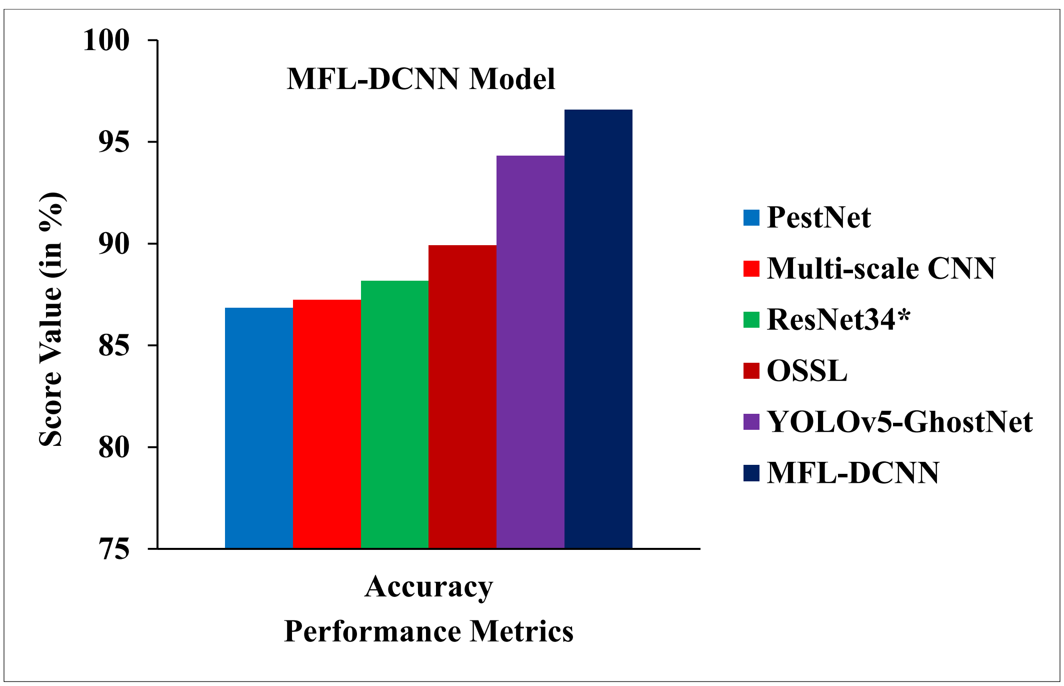

Fig. 6.17 Accuracy Comparison of MFL-DCNN Model

The effectiveness of several classifier models used to categorize leaf diseases and pests on the investigated multi-dimensional dataset. As can be shown in Fig. 6.4, the MFL-DCNN improves accuracy by 11.2% compared to the PestNet model, 10.7%

compared to the multi-scale CNN model, 9.5 compared to the ResNet34* model, 7.4% compared to the OSSL model, and 2.4% compared to the YOLOv5-GhostNet model. This is achieved because of using multiple information like soil factors, leaf image characteristics, pest data and weather parameters during training the DCNN classifier.

Thus, this comparison scrutiny clarifies that the MFL-DCNN ensures the greatest classification effectiveness than another classifier executed on the given multi-dimensional data. In terms of accuracy, the MFL-DCNN is useful for classifying the pest related to the variety of leaf diseases from various crops.

6.6 SUMMARY

In summary, this chapter provides an overview of the advantages of ensemble learning and methods for dealing with characteristics that exist on several dimensions. The ideation and development of a novel MFL-DCNN classification model are also described in depth. The effectiveness of the models is evaluated across a range of leaf-affecting diseases and pests.