International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Visual Phenotype Manifold Reconstruction for Early Foliar Abnormality Analysis in Cauliflower Imaging Systems

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Abstract
Early identification of leaf-related infections in cauliflower is crucial for reducing crop damage and ensuring stable agricultural output. Traditional inspection techniques, which depend on human observation, are often inconsistent, labour intensive, and unsuitable for large farming environments. To overcome these challenges, this research introduces an intelligent hybrid framework combining Machine Learning (ML), Deep Learning (DL), and Transfer Learning (TL) for automated cauliflower leaf disease recognition. The proposed Cauliflower Leaf Disease Classification (CLDC) system utilizes a curated dataset categorized into eleven disease classes. Image preprocessing involves resizing to 64×64 pixels and normalization to enhance model performance. A novel Inception Residual Network-based Convolutional Neural Network (IRN-CNN) is designed to extract high-level discriminative features using customized inception-residual modules. These deep features are further processed using Logistic Regression (LR) to improve classification accuracy and generalization. For performance benchmarking, conventional models such as Decision Tree Classifier (DTC), Artificial Neural Network (ANN), and standalone LR are also implemented. The system is integrated into a Tkinter-based Graphical User Interface (GUI), enabling functionalities such as dataset upload, preprocessing, training, evaluation, and real-time prediction. Batch image analysis with CSV export support enhances usability for large-scale applications. Additionally, an Explainable Artificial Intelligence (XAI) component powered by a generative AI API provides detailed insights, including disease severity, affected regions, and crop verification. A Telegram Bot interface further extends accessibility for mobile-based detection. Experimental findings confirm that the proposed IRN-CNN hybrid model delivers superior accuracy and reliability, making it a scalable solution for smart agriculture and precision farming systems.

Keywords: Cauliflower Leaf Disease, Plant Disease Detection, Image Classification, Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), Inception Residual Network (IRN-CNN)

1. Introduction

The rapid increase in global population, coupled with industrial expansion, has significantly reduced the availability of cultivable land, posing a major threat to food security. Current projections indicate that food production must increase by nearly 70% to satisfy future demand [1]. This challenge is more pronounced in developing regions such as Asia and Africa, where agriculture predominantly depends on small-scale landholdings. Simultaneously, environmental constraints and stricter sustainability policies restrict the expansion of agricultural areas and discourage deforestation practices [2]. Consequently, the per capita availability of arable land continues to decline, emphasizing the urgent need for innovative and resource-efficient agricultural solutions. Conventional strategies aimed at increasing crop yield such as selective breeding, genetically modified crops, and the extensive use of fertilizers and pesticides have shown considerable success in boosting productivity. However, these approaches often raise concerns regarding environmental degradation, soil health, and long-term ecological balance. This has led to a growing emphasis on sustainable agricultural practices that enhance productivity while minimizing environmental impact [3]. One effective strategy to improve land-use efficiency is the cultivation of multiple crops within a single year, particularly in regions with favorable agro-climatic conditions. This can be achieved through sequential cropping or simultaneous cultivation of short-duration crops [4].

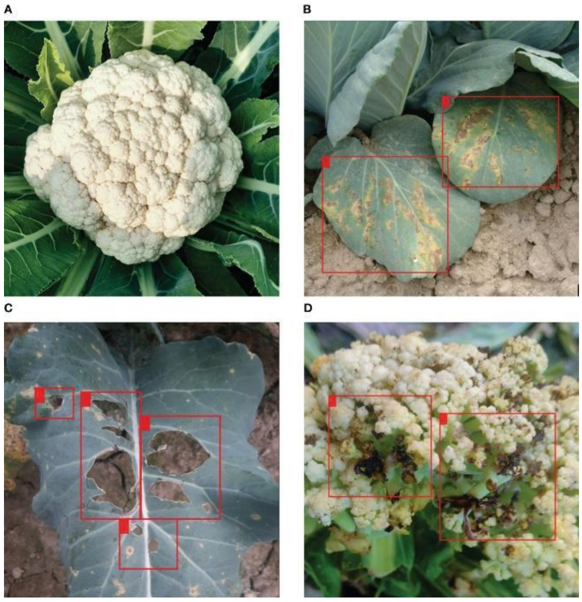

Figure. 1: Cauliflower leaf diseases.

In this context, maintaining biodiversity and promoting ecological balance are critical elements of sustainable farming systems [5]. Intercropping, a widely adopted practice, involves growing two or more crops together on the same field during the same growing season [6][7]. This technique offers multiple benefits, including improved resource utilization, enhanced productivity compared to monocropping, as shown in figure 1 better pest and disease control, increased soil fertility, and reduced soil erosion. Moreover, intercropping contributes to economic stability for farmers by minimizing the risks associated with crop failure [8]. However, careful selection of compatible crop combinations is essential to avoid resource competition and to ensure mutual growth benefits and higher economic returns [9].

Cauliflower (Brassica oleracea var. botrytis) is a nutritionally rich vegetable belonging to the Brassicaceae family, known for its high content of vitamins, minerals, and bioactive compounds. Similarly, leaf lettuce (Lactuca sativa L. var. crispa) plays a significant role in human nutrition. Both crops thrive in cool climatic conditions and are widely cultivated, particularly in countries like Turkey, where annual production reaches approximately 235,000 tons (9100 ha) for cauliflower and 234,000 tons (9600 ha) for lettuce. In the face of shrinking agricultural land, enhancing yield per unit area through efficient and sustainable practices has become a critical focus in modern agricultural systems [10].

2. Literature Survey

Soengas et al. [11] reported that plants respond to thermal stress by activating protective biochemical mechanisms, particularly through the enhanced synthesis of phenolic compounds. This adaptive response is regulated by balancing anabolic and catabolic pathways, leading to increased accumulation of phenolics that function as antioxidants. These compounds play a vital role in mitigating oxidative damage caused by elevated temperatures, thereby improving plant tolerance under stress conditions. Chen et al. [12] conducted a comprehensive review on Chinese kale and highlighted the significant role of polyamines (PAs) in plant stress physiology. Their findings suggest that PAs contribute to maintaining cell membrane stability during heat stress, thereby preserving cellular integrity.

Additionally, PAs are involved in regulating stress-responsive pathways, enabling plants to adapt more effectively to high-temperature environments.

Collado-González et al. [13] emphasized the importance of developing innovative strategies to counteract the adverse effects of climate change on crop systems. Their study investigated cauliflower by-products treated with putrescine under extreme temperature conditions across two CO2 levels (400 ppm and 1000 ppm). The results demonstrated notable changes in biomass and antioxidant composition, indicating that exogenous treatments can enhance plant resilience while also promoting the utilization of agricultural by-products. Singh et al. [14] examined the impact of preharvest arginine application on cauliflower quality attributes. Their study revealed that arginine treatment can delay undesirable color changes, helping maintain the preferred white appearance of cauliflower curds. Since consumer acceptance largely depends on visual quality, such treatments play a crucial role in improving market value and shelf life.

Cunningham et al. [15] analysed mineral composition changes in cauliflower under heat stress conditions. Their findings align with earlier studies, indicating that elevated temperatures significantly influence nutrient uptake and distribution in plants. Heat stress was observed to alter mineral concentrations, which can affect both plant growth and nutritional quality. Kamiab et al. [16] investigated the physiological effects of arginine application under stress conditions and reported a reduction in sodium (Na^+) accumulation, chloride (Cl^-) levels, and the Na^+/K^+ ratio. Additionally, moderate heat stress combined with arginine treatment resulted in increased accumulation of Cl^- and nitrate. The study also highlighted that arginine serves as a precursor for polyamines, glutamine, and nitric oxide (NO), all of which are essential signaling molecules involved in stress response mechanisms.

Singh et al. [17] demonstrated that cauliflower exhibits considerable adaptability to varying temperature and humidity conditions. However, their findings indicated that foliar application of arginine did not significantly affect most growth and quality parameters, except for slight variations in color attributes (L* value). These observations are consistent with previous studies, suggesting limited but specific effects of arginine under certain conditions. Collado-González et al. [18] reviewed the increasing global consumption of cauliflower due to its health-promoting properties, particularly in preventing chronic diseases. Their study further explored the role of arginine in enhancing heat stress tolerance by boosting polyamine synthesis. The results confirmed that exogenous arginine application positively influences both physical and biochemical quality traits of cauliflower under stress conditions.

Turan et al. [19] investigated intercropping systems involving cauliflower and leaf lettuce under varying nitrogen fertilization levels (160, 200, and 240 kg N ha^{-1}). Their results demonstrated that intercropping significantly improved agronomic parameters such as chlorophyll content (SPAD), plant biomass, head size, and overall yield. Increased nitrogen application further enhanced these parameters in both monocropping and intercropping systems, highlighting the effectiveness of integrated nutrient management. Olsen et al. [20] focused on soil property analysis and standard measurement techniques relevant to agricultural studies. Electrical conductivity (EC) was measured using saturation extracts, while soil pH was determined in 1:2 soil-water suspensions. Calcium carbonate content, organic matter (OM), and exchangeable cations were analysed using established methods, including ammonium acetate extraction. Additionally, micronutrient levels were assessed using diethylenetriaminepentaacetic acid (DTPA) extraction, providing essential insights

3. Proposed Methodology

The proposed methodology introduces a comprehensive analytical framework for detecting and classifying diseases in cauliflower plants using advanced artificial intelligence techniques. The analytical pipeline begins with image acquisition and dataset organization, where cauliflower leaf

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images are collected and structured into disease-specific categories. This is followed by image preprocessing, including resizing, normalization, and pixel scaling, to ensure uniformity and compatibility with computational models. Deep feature extraction is performed using a customized convolutional architecture inspired by Inception-ResNet principles, which captures critical visual characteristics such as lesion patterns, discoloration, and texture variations. These extracted representations are then utilized by multiple machine learning classifiers to perform accurate disease categorization. In addition, an explainable image analysis component is integrated to validate whether the input image corresponds to a cauliflower plant and to provide descriptive insights before classification. A graphical interface supports user interaction for data handling, model training, evaluation, and prediction tasks, as illustrated in Figure 2. A lightweight storage mechanism manages trained models and authentication data, while an integrated communication module enables remote image-based analysis. Continuous evaluation and retraining further enhance the adaptability and performance of the analytical framework.

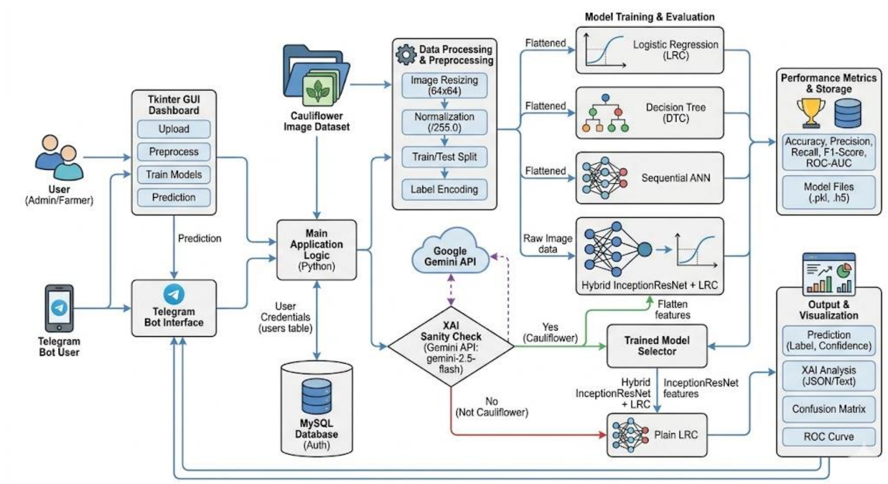

Figure. 2: System architecture

User Interface (Client Application)

- The user interacts with the system through a desktop-based graphical interface developed using a GUI framework.
- The interface provides functionalities such as user authentication, dataset upload, preprocessing, model training, performance comparison, and prediction.
- Users can select cauliflower leaf images from local storage and submit them for disease analysis.
- All user actions are processed through the interface and forwarded to the backend processing modules.

Application Communication Layer

- A communication module enables interaction between the client interface and backend analytical components.
- It manages the flow of image data, prediction requests, and result responses within the system.
- This layer ensures seamless execution of the prediction pipeline for both local and remote inputs.
- It also supports real-time processing and response delivery.

Database (Authentication Storage)

- A lightweight database system is used to store user authentication details securely.

- It maintains records of registered users including usernames, encrypted passwords, and access roles.
- The database supports login verification and user management operations.
- Its efficient storage mechanism ensures fast data retrieval and persistence.

Image Dataset (Cauliflower Disease Collection)

- The dataset serves as the primary source of input images for the analytical pipeline.
- It contains labeled images of cauliflower leaves categorized into multiple disease classes.
- The dataset captures diverse visual features such as leaf texture, discoloration, fungal patterns, and structural damage.
- It is used for both training and evaluating classification models.

Image Preprocessing and Feature Extraction

- The input images undergo preprocessing operations such as resizing, normalization, and pixel value transformation.
- A deep convolutional architecture based on Inception-ResNet principles is used to extract meaningful visual features.
- This model captures complex spatial and texture-based patterns associated with different diseases.
- The output is converted into feature vectors that serve as input for classification models.

ML and DL Classification Models

- The extracted feature vectors are analysed using multiple classification models:
  - Logistic Regression: Performs probabilistic classification based on learned feature weights.
  - Decision Tree: Uses hierarchical decision rules to classify disease patterns.
  - Artificial Neural Network (ANN): Learns complex nonlinear relationships for improved prediction.
  - Hybrid InceptionResNet + Logistic Regression: Combines deep feature extraction with classical classification for enhanced accuracy.
- Each model independently predicts the disease category for comparative analysis.

Explainable Image Analysis Module

- The system integrates an explainable AI module to validate the input image.
- It determines whether the image belongs to a cauliflower plant before classification.
- The module provides additional insights such as disease presence, severity, and affected plant region.
- This improves transparency, interpretability, and reliability of the analytical process.

Prediction Results and Output Generation

- The system generates predictions indicating the disease category of the input image.
- Results are displayed within the graphical interface along with visual representations.
- Output may include confidence scores and detailed analytical insights.
- Comparative performance metrics are also presented for better understanding.

Remote Image Prediction Workflow

- The framework supports remote interaction through a communication mechanism.
- External systems can send images for analysis and receive predictions.
- The system processes incoming images using trained models and returns structured outputs.
- This enables real-time disease detection in distributed environments.

Model Evaluation and Retraining

- Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score.

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- Visualization tools like confusion matrices and ROC curves are used for detailed analysis.
- The system supports retraining with new data to improve accuracy over time.
- This continuous learning capability ensures adaptability to evolving disease patterns.

4. Dataset Description

The dataset used in this research consists of cauliflower leaf images collected from multiple disease categories to support automated foliar disease classification. Each disease class is stored in a separate folder, allowing the system to automatically identify and label categories during preprocessing. The images were captured under diverse real-world conditions, including variations in lighting, background, infection stage, and leaf orientation. Such diversity ensures that the model learns robust visual patterns that generalize well to unseen samples. All images are provided in standard formats like JPG and PNG, making them compatible with OpenCV-based image loading. Before training, every image is resized to a fixed dimension of 64×64 pixels and normalized to ensure uniformity across models. This structured and well-labelled dataset forms the foundation for accurately training the hybrid DL model for cauliflower disease detection.


(A)


(B)


(C)

Figure. 3 (A), (B), and(c): Dataset images of club root, cabbage aphid colony, alternaria leaf spot

The dataset images in Figure 3 represent three distinct cauliflower disease conditions: club root, cabbage aphid colony, and Alternaria leaf spot. Figure 3 (A) shows a cauliflower plant affected by club root, characterized by swollen, irregular, and club-shaped roots that hinder the plant's ability to absorb water and nutrients, leading to yellowing, wilting, and overall stunted growth. Figure 3 (B) depicts a cabbage aphid colony on a leaf surface, where clusters of pale gray, waxy aphids can be seen feeding on plant sap, causing leaf curling, discoloration, and weakening of the plant while also increasing the risk of secondary infections due to honeydew secretion. Figure 3 (C) illustrates Alternaria leaf spot, showing numerous dark circular lesions with distinctive concentric rings and surrounding yellow halos; some spots have cracked centers, indicating tissue decay caused by the fungal pathogen. Together, these

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images visually capture the symptoms and damage associated with major cauliflower diseases included in the dataset, as shown in table 1.

Table. 1: Dataset description for cauliflower foliar diseases

SI. No	Disease Name	Image Count	Description
1	Alternaria Leaf Spot	100	A fungal disease caused by Alternaria brassicae leading to circular brown or dark spots on cauliflower leaves. These lesions often have concentric rings and can rapidly expand under humid conditions. Severe infections reduce leaf area and overall plant vigor.
2	Bacterial Soft Rot	100	A destructive disease caused by Pectobacterium carotovorum, leading to water-soaked spots and tissue collapse. The affected areas turn mushy, foul-smelling, and soft due to enzymatic breakdown. It spreads quickly through wounds and high moisture environments.
3	Black Leg	105	Caused by the fungus Leptosphaeria maculans, leading to dark lesions at the stem base or leaf petioles. Infection weakens the plant's vascular tissues, reducing nutrient flow. Severe cases result in plant lodging and reduced yield.
4	Black Rot	103	A bacterial disease caused by Xanthomonas campestris, forming V-shaped yellow lesions on leaf edges. The infection travels along the veins, causing blackening and tissue death. It spreads rapidly under warm, humid conditions.
5	Cabbage Aphid Colony	120	Caused by colonies of Brevicoryne brassicae, which suck sap from leaf surfaces. Infestation leads to yellowing, curling, and stunted growth. The presence of honeydew also promotes secondary fungal infections.
6	Cauliflower Mosaic	99	A viral disease caused by Cauliflower Mosaic Virus (CaMV), leading to mosaic patterns, mottling, and distorted leaves. The virus interferes with chlorophyll production and disrupts photosynthesis. Infected plants exhibit stunted growth and poor head formation.
7	Club Root	100	A soil-borne disease caused by Plasmodiophora brassicae, resulting in swollen, club-shaped roots. Plants show wilting, yellowing, and stunted growth even with adequate water. The pathogen persists in soil for years.
8	Downy Mildew	100	A fungal-like pathogen (Hyaloperonospora parasitica) causing yellow patches on upper leaf surfaces with white, fluffy growth underneath. Infection spreads through moisture and cool weather. Severe cases lead to leaf drop and reduced productivity.
9	Powdery Mildew	104	Caused by Erysiphe cruciferarum, forming white powdery fungal growth on leaf surfaces. It reduces photosynthesis and weakens plant vigor. Infection spreads rapidly in dry, warm conditions.

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10	Ring Spot	100	A fungal disease caused by Mycosphaerella brassicicola, producing circular lesions with concentric rings. These spots expand and coalesce under cold, wet conditions. Severe infections reduce leaf quality and yield.
11	White Rust	104	Caused by *Albugo candida*, producing white pustules on leaf undersides and distorted leaf structures. The pathogen thrives in cool, moist environments. Heavily infected plants show reduced leaf area and poor head formation.

9.3 Results description

The results obtained from the analytical framework demonstrate the effectiveness of artificial intelligence techniques in accurately identifying diseases in cauliflower plants. Multiple classification models were evaluated to analyse their predictive performance using standardized metrics such as accuracy, precision, recall, and F1-score. The experimental outcomes indicate that deep learning–based and hybrid approaches outperform traditional models by capturing complex visual patterns present in leaf images. Confusion matrix and ROC curve analyses further validate the reliability and consistency of the predictions across different disease classes. The integration of the explainable analysis component enhances the interpretability of results by providing additional insights such as disease severity and affected regions. Batch prediction and real-time evaluation capabilities confirm the system's applicability in practical agricultural scenarios.

Figure 4 presents the confusion matrices for four different classifiers applied to the cauliflower leaf disease dataset. The confusion matrix exhibits perfect diagonal dominance with all classes correctly classified. There are no misclassifications, demonstrating that the IRNCNN effectively extracts hierarchical and subtle leaf features. This confirms the model's superior capability for multi-class disease detection, ensuring reliable and real-time support for farmers and agricultural experts.

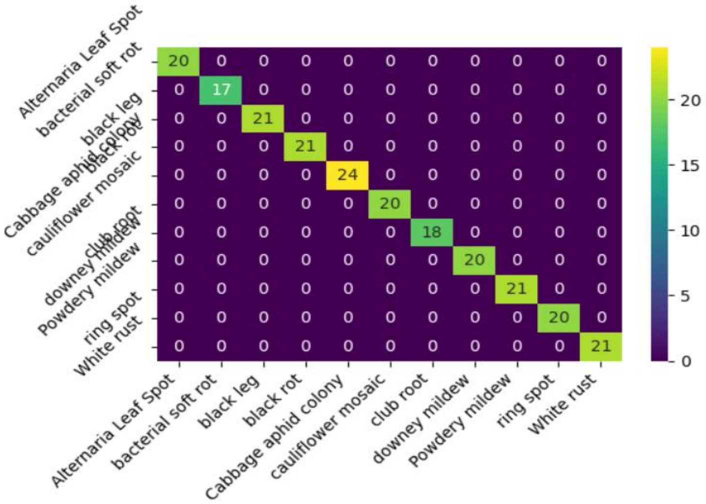

Figure. 4: Obtained confusion matrix of various mode for IRNCNN.

Received: 07-05-2026 | Accepted: 14-06-2026 | Published: 22-06-2026

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DATA SCIENCE AND IOT MANAGEMENT SYSTEM
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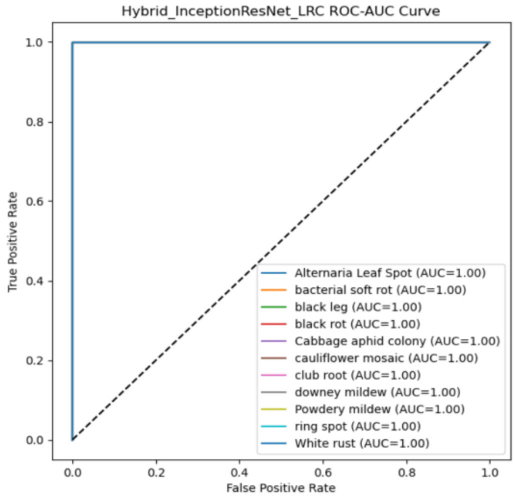
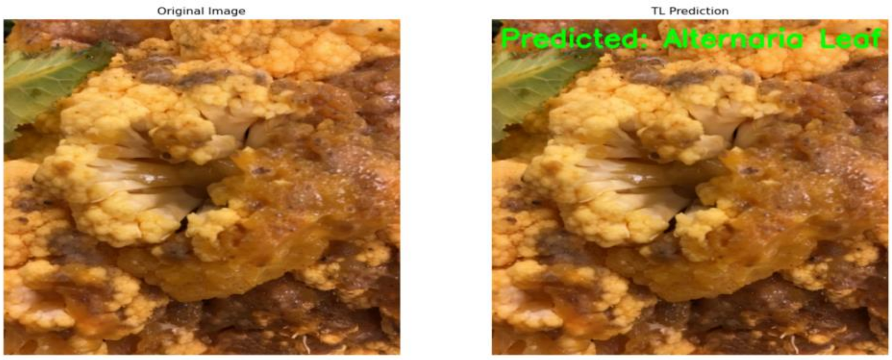


Figure. 5: Obtained ROC-AUC curve of various mode for IRNCNN

Figure 5 illustrates the ROC-AUC curves hybrid IRNCNN: The ROC-AUC curves reach the maximum value of 1.0 for all eleven disease classes. This indicates flawless discrimination between classes, demonstrating that the IRNCNN successfully extracts high-level hierarchical features from cauliflower leaf images. The results confirm the model's robustness and suitability for real-time disease detection, enabling precise decision-making for farmers and agricultural practitioners.

Figure 6 demonstrates the Leaf Guard AI system performing inference on a single cauliflower leaf image. The input image is pre-processed to standardize size, normalize pixel values, and enhance relevant leaf features. Figure 6 (a) Bacterial Soft Rot. The input leaf exhibits tissue softening and discoloration patterns. The IRNCNN model correctly identifies the characteristic water-soaked lesions and classifies the leaf with high confidence.

(a)



(b)

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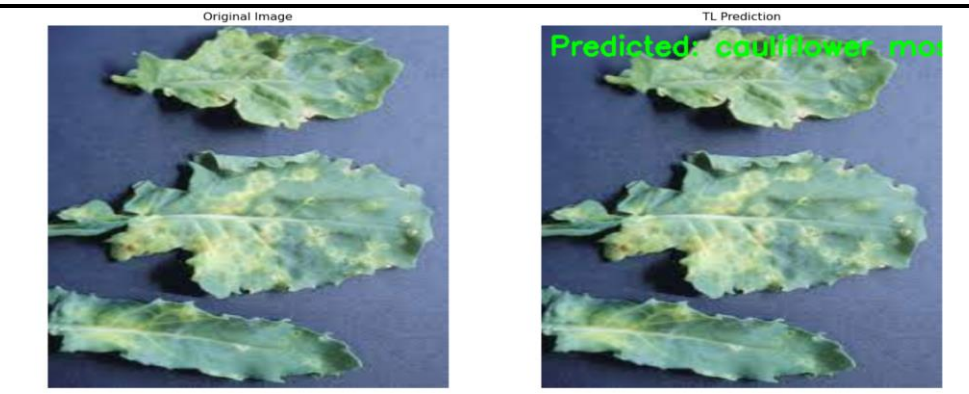

(c)

(d)

Figure. 6: Predictions on single test Image. (a) bacterial soft rot, (b) Alternaria Leaf Spot, (c) cauliflower mosaic, (d) Cabbage aphid colony.

Figure 6 (b) Alternaria Leaf Spot. The leaf shows small, dark circular spots with yellow halos. The model extracts fine-grained textural features to accurately detect the infection.

Figure 6 (c) Cauliflower Mosaic. Symptoms include mosaic-like discoloration across the leaf surface. The hierarchical feature extraction captures both the irregular vein patterns and color variations, enabling precise classification.

Figure 6 (d) Cabbage Aphid Colony. The leaf surface displays visible insect clusters. The model detects the aggregated aphid patterns and distinguishes this pest-related disease from fungal and bacterial infections.

Figure. 7: Batch Predictions on Test Images

Figure 7 showcases the system performing batch processing on multiple leaf images simultaneously. The model processes each image through the preprocessing and feature extraction pipeline, followed by disease classification for all samples in a single execution. The results are displayed in a tabular or visual format showing predicted classes and confidence levels for each leaf. Batch predictions reduce

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processing time for large datasets, enabling farmers and researchers to monitor multiple plants quickly, ensuring timely detection of infections across a field.

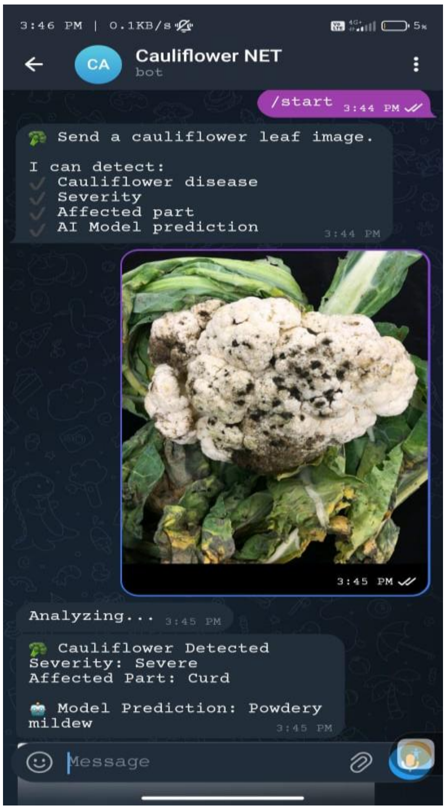

Figure. 8: Predictions with telegram bot

Figure 8 illustrates the integration of the Leaf Guard AI system with a Telegram Bot interface. Users upload cauliflower leaf images directly from their mobile devices, and the IRNCNN model performs real-time disease detection. The system returns the predicted disease along with relevant diagnostic information, including confidence scores and suggested management actions. This mobile-accessible deployment demonstrates the system's practical applicability in field conditions, supporting farmers with immediate decision-making without requiring desktop access or expert intervention.

Table. 2: Performance comparison of classification models

Classifier Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR	0.9148	0.9271	0.9162	0.9175
DT	0.5471	0.7834	0.5486	0.5840
ANN	0.2287	0.2620	0.2187	0.1480
IRNCNN	1.0000	1.0000	1.0000	1.0000

Table 1 presents a comparison of four classifiers applied to cauliflower leaf disease detection. The LR model achieves high accuracy of 91.48% and demonstrates good overall performance, but struggles with subtle variations such as Powdery mildew and cauliflower mosaic. The DT model performs well on visually distinct classes but shows poor generalization for similar-looking diseases, resulting in an accuracy of 54.71%. The ANN model fails to learn discriminative features for multi-class classification, producing the lowest accuracy of 22.87% and misclassifying multiple disease types. In contrast, the proposed IRNCNN achieves perfect performance with 100% accuracy, precision, recall, and F1-score, effectively capturing both hierarchical and subtle features in leaf images. These results highlight the superiority of IRNCNN for automated, real-time disease identification in cauliflower crops, demonstrating robustness, high generalization, and suitability for practical deployment. The comparison clearly shows that deep learning outperforms traditional ML classifiers in handling complex visual patterns of multiple foliar diseases.

5. Conclusion

The CLDC system demonstrates an efficient and automated approach for detecting cauliflower foliar diseases using ML and DL techniques. Preprocessing ensures standardized and noise-free inputs, enabling accurate pattern learning. While LR, DT, and ANN provide baseline performance, the hybrid IRNCNN improves accuracy through deep feature extraction and better generalization. The system supports both batch prediction and real-time inference, making it practical for field use. A Tkinter-based GUI enhances usability, allowing non-technical users to operate the system easily. Integration of a Telegram bot enables remote image-based prediction, increasing accessibility. The use of an external AI API provides explainable outputs such as disease severity and affected regions. The system functions as a reliable and scalable solution for agricultural disease detection.

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