Exploring Hybrid Convolutional Representations for Early-Stage Foliar Disease Recognition in Cauliflower

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ABSTRACT

Early detection of foliar diseases in cauliflower crops is essential for minimizing yield loss and improving agricultural productivity. Conventional disease identification methods rely on manual inspection, which is often subjective, time-consuming, and impractical for large-scale monitoring. To address these limitations, intelligent systems based on Machine Learning (ML) and Deep Learning (DL) have emerged as effective solutions for automated and accurate disease diagnosis. This study presents a Transfer Learning (TL)-based framework for multi-disease in Cauliflower Leave Disease Classification (CLDC), integrating both DL and traditional ML approaches within a unified system. The dataset is preprocessed by resizing images to 64×64 pixels, normalizing pixel values, and organizing them into eleven disease categories. A hybrid Inception Residual Network Convolutional Neural Network (IRNCNN) model is developed using Convolutional Neural Networks (CNN), where deep features are learned through customized inception-residual blocks. The extracted features are subsequently classified using Logistic Regression (LR) to improve classification performance. In addition, baseline models including LR, Decision Tree Classifier (DTC), and Artificial Neural Network (ANN) are implemented to enable comparative evaluation. The system is deployed using a Tkinter-based Graphical User Interface (GUI), supporting dataset upload, preprocessing, model training, evaluation, and prediction. Batch prediction on image folders is also supported, with results exported in CSV format. Furthermore, an Explainable Artificial Intelligence (XAI) module is integrated to analyze input images, verify whether they correspond to cauliflower, and provide insights such as disease severity and affected plant parts. A Telegram Bot interface is incorporated to enable real-time mobile-based disease detection and user interaction. Experimental results demonstrate that the proposed IRNCNN model achieves high classification accuracy and robust performance across multiple disease categories. The integration of DL-based feature extraction, ML-based classification, XAI analysis, and multi-platform deployment establishes the system as a scalable and effective solution for real-time crop disease monitoring and precision agriculture.

Key words: Cauliflower Leaf Disease Classification (CLDC), Transfer Learning (TL), Deep Learning (DL), Machine Learning (ML), Image Classification, Plant Disease Diagnosis.

1. INTRODUCTION

The continuous decline in available arable land, driven by rapid population growth and expanding industrial activities, has created significant challenges for global food production. It is estimated that nearly 70% additional food will be required to meet the demands of the growing population [1]. This issue is particularly critical in regions such as Asia and Africa, where agricultural activities are largely dependent on small landholdings. At the same time, increasing environmental concerns and strict sustainability regulations limit the expansion of agricultural land and discourage practices such as deforestation. As a result, the amount of cultivable land per person is steadily decreasing, intensifying the need for more efficient farming strategies. To meet rising food demands, various approaches have been adopted, including crop improvement through breeding techniques, the use of genetically modified organisms, and the application of chemical fertilizers and pesticides. While these methods have contributed to increased productivity, they often raise concerns related to environmental sustainability and ecological balance. Therefore, there is a growing need for agricultural practices that enhance productivity while remaining environmentally responsible and aligned with sustainable agriculture principles [2].

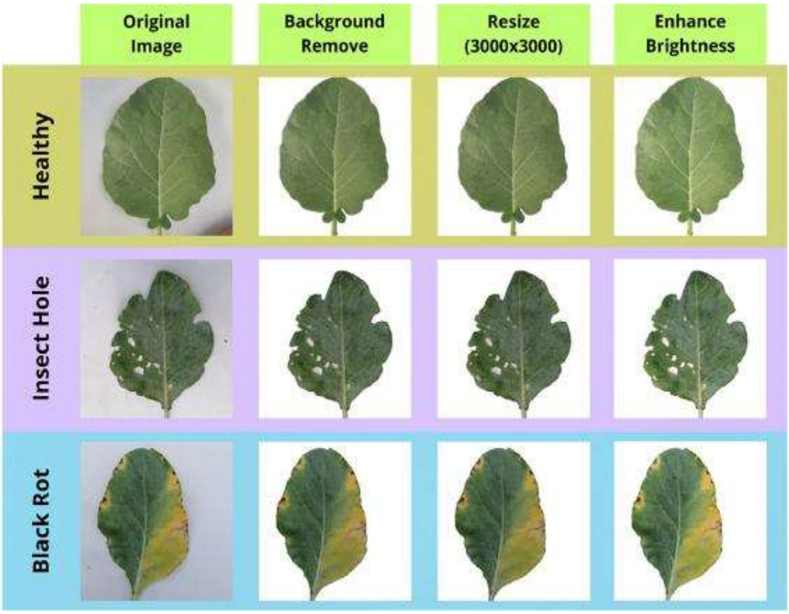


Fig. 1: Cauliflower foliar diseases

One such approach involves maximizing land utilization by cultivating multiple crops within a year, especially in regions with favorable climatic conditions. This can be achieved through the sequential or simultaneous cultivation of short-duration crops [3]. Maintaining agricultural diversity and managing it effectively are also essential components of sustainable farming systems. Sustainable agriculture emphasizes the use of natural processes to design efficient and resilient farming practices. Intercropping is one such technique that promotes biodiversity within agricultural systems. It involves growing two or more crops together in the same field during the same growing period. This method offers several advantages, including better utilization of environmental resources, higher productivity compared to monocropping, improved pest and disease management, enhanced soil fertility, reduced erosion, and increased overall land-use efficiency. Additionally, intercropping helps stabilize farmers' income by reducing risks associated with crop failure [4,5]. However, the selection of compatible crop species is crucial; the companion crops should not compete negatively with the primary crop but instead support its growth and improve overall economic returns. Cauliflower (Brassica oleraceae var. botrytis), a member of the

Brassicaceae family, is recognized for its high nutritional value, providing essential vitamins, minerals, and phytochemicals. Similarly, leaf lettuce (Lactuca sativa L. var. crispa) is an important vegetable contributing to human nutrition. Both crops are well-suited to cool climatic conditions and are widely cultivated in Turkey, with annual production figures of approximately 235,000 tons (9100 ha) for cauliflower and 234,000 tons (9600 ha) for lettuce. Given the limitations in expanding agricultural land, improving productivity per unit area has become a key priority in modern agriculture [6].

2. LITERATURE SURVEY

2.1 RELATED WORK

2.1.1 Agronomic Importance and Global Production of Cauliflower

Cauliflower is a widely cultivated vegetable crop belonging to the Brassicaceae family and is valued for its nutritional richness and economic importance. Nimkar et al. [7] described it as the "aristocrat of cole crops" due to its high consumer demand and superior quality characteristics. The crop is cultivated across diverse climatic regions, reflecting its adaptability and global significance.

Akter et al. [8] highlighted the global production scenario, reporting that total production reached 25.50 million metric tons in 2020, with Asia contributing approximately 75% of the total output. Countries such as Bangladesh play a major role in production, indicating the importance of developing nations in sustaining global supply chains. These studies collectively emphasize cauliflower's role as a major agricultural commodity with both nutritional and economic value.

2.1.2 Plant Growth Regulators and Yield Enhancement

The application of plant growth regulators has been extensively studied to improve yield and reproductive performance in cauliflower cultivation. Prodhan et al. [9] investigated the effects of GA3 at different concentrations and application stages on seed production. The study revealed that both concentration levels and timing significantly influence reproductive efficiency and overall yield.

The findings suggest that optimized use of GA3 enhances flowering, seed formation, and plant vigor. Such approaches provide practical strategies for improving productivity, especially in controlled cultivation environments. These results highlight the importance of integrating growth regulator management into modern agricultural practices.

2.1.3 Environmental Stress and Developmental Sensitivity

Environmental factors, particularly temperature, play a crucial role in determining crop performance. Santos et al. [11] reported that heat stress during the flower bud differentiation stage causes significant damage to crop development, whereas stress applied after bud formation has a comparatively lower effect. This indicates that the timing of environmental stress exposure is critical.

The response of crops to temperature variations depends on multiple factors, including crop variety, intensity of stress, duration, and growth stage. Understanding these interactions is essential for developing adaptive cultivation strategies that minimize yield loss under changing climatic conditions.

2.1.4 Biochemical Responses to Heat Stress

Plants activate various biochemical mechanisms to cope with thermal stress. Soengas et al. [12] reported that heat stress induces increased biosynthesis of phenolic compounds through regulation of metabolic pathways. These compounds act as antioxidants, protecting plant cells from oxidative damage.

Chen et al. [13] further emphasized the role of PAs in enhancing stress tolerance by maintaining membrane integrity and stabilizing cellular structures. The accumulation of such compounds enables plants to adapt to adverse environmental conditions, improving survival and productivity.

2.1.5 Analytical Techniques for Plant Metabolite Assessment

Accurate analysis of plant metabolites is essential for understanding physiological responses under stress conditions. Balibrea et al. [10] described a biochemical extraction method involving methanol–water solutions and C18 cartridge filtration to isolate antioxidant compounds from plant tissues.

This methodology enables precise quantification of bioactive compounds, facilitating detailed investigation of plant responses to environmental stress and treatment conditions. Such analytical techniques are fundamental for advancing research in plant physiology and stress biology.

2.1.6 Climate Change Adaptation and Sustainable Practices

The impact of climate change on crop production has led to increased focus on sustainable agricultural practices. Collado-González et al. [14] studied the effects of putrescine treatment under different CO_2 conditions (400 ppm and 1000 ppm) and found improvements in biomass and antioxidant accumulation.

These findings suggest that combining biochemical treatments with environmental management strategies can enhance crop resilience. Such approaches are essential for ensuring sustainable production under future climate scenarios.

2.1.7 Preharvest Treatments and Quality Maintenance

Maintaining crop quality is critical for market acceptance and economic value. Singh et al. [15] reported that preharvest application of arginine helps delay yellowing and preserves the desirable white color of cauliflower curds. Quality attributes such as color, compactness, and absence of defects are key factors influencing consumer preference.

3. PROPOSED SYSTEM

The system is a Tkinter-based GUI application for cauliflower leaf disease detection that allows admin and farmer users to upload datasets, preprocess images with the resizing and normalization, and build multiple models such as LR, DTC, ANN, and a hybrid IRNCNN, which are stored for later use. A prediction engine loads these trained models to perform single or batch image classification, while results are visualized through plots like confusion matrix and ROC curves and displayed within the interface or exported as CSV. The system also integrates a Telegram bot for remote image-based predictions and connects to an external XAI service to generate explainable outputs such as disease type, severity, and affected plant parts as illustrated in Fig. 2.

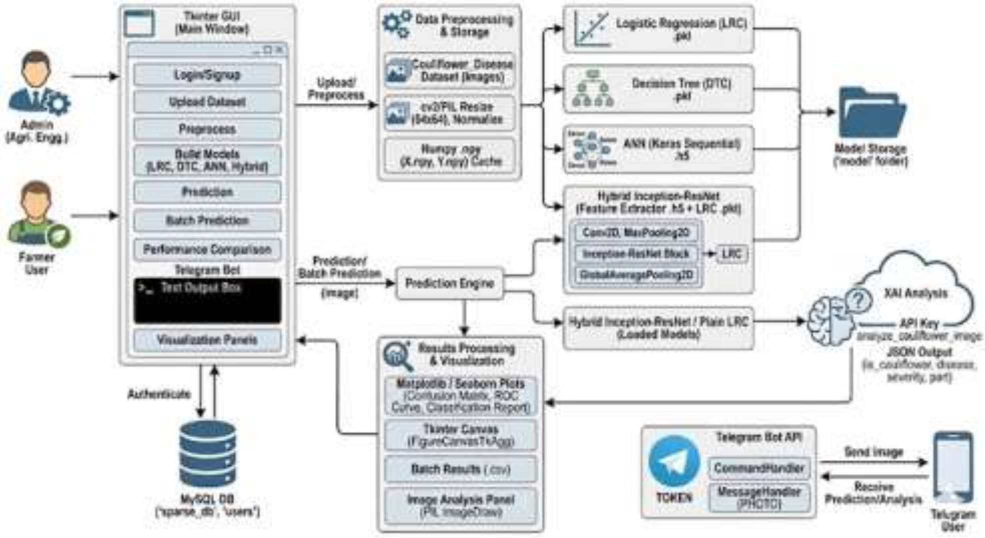


Fig. 2: System architecture for cauliflower foliar diseases

User Interface & Authentication: The system begins with a Tkinter-based GUI where admin and farmer users log in and access features like dataset upload, preprocessing, and prediction. User credentials are securely managed using a MySQL database.

Data Upload & Preprocessing: Users upload cauliflower leaf images, which are resized (e.g., 64×64) and normalized using OpenCV. The processed data is stored as NumPy arrays to improve efficiency during training and prediction.

Model Training & Storage: Multiple models such as LR, DTC, ANN, and a hybrid IRNCNN are trained on the dataset. The trained models are saved in a designated folder for reuse without retraining.

Prediction Engine: The system loads the trained models to perform single or batch predictions on new images. It processes input images and outputs disease classification results using the selected model.

Results Visualization & Export: Prediction outcomes are visualized using plots like confusion matrix and ROC curves via Matplotlib & Seaborn. Results are displayed in the GUI and can also be exported as CSV files for further analysis.

External Integration & Explainability: The system integrates with a Telegram bot for remote image-based predictions and connects to an XAI service. This provides explainable insights such as disease type, severity, and affected plant regions.

4. RESULTS DESCRIPTION

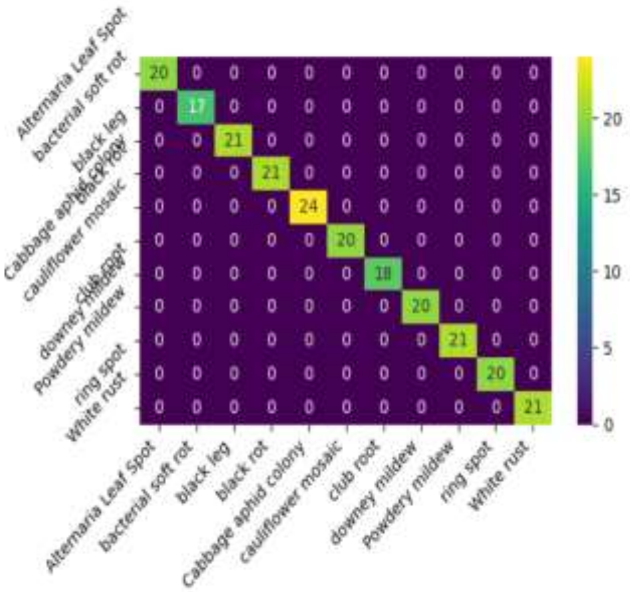


Fig. 3: Obtained confusion matrix of IRNCNN model

Fig. 3 illustrates the obtained confusion matrix of the IRNCNN model, representing the classification performance across different disease classes of cauliflower leaves, including Alternaria leaf spot, bacterial soft rot, black leg, black rot, cabbage aphid colony, cauliflower mosaic, club root, downy mildew, powdery mildew, ring spot, and white rust. The matrix clearly shows that the model achieves highly accurate predictions, with all samples correctly classified along the diagonal entries such as 20, 17, 21, 24, 20, 18, and 21 for the respective classes. The off-diagonal elements are entirely zero, indicating that there are no misclassifications among the disease categories. This demonstrates that each class is perfectly distinguished without any overlap or confusion.

Fig. 4 depicts the ROC-AUC curve of the IRNCNN model, illustrating its performance across the same different disease classes, including Alternaria leaf spot, bacterial soft rot, black leg, black rot, cabbage aphid colony, cauliflower mosaic, club root, downy mildew, powdery mildew, ring spot, and white rust. The curve shows that the AUC values for all classes are equal to 1.00, indicating perfect classification capability for each category. The model maintains a true positive rate of 1.0 while keeping the false positive rate at 0.0 across all thresholds. This reflects ideal separability between classes with no overlap in predictions. The uniformity of the ROC curves across all disease classes further highlights the model's consistency and generalization ability.

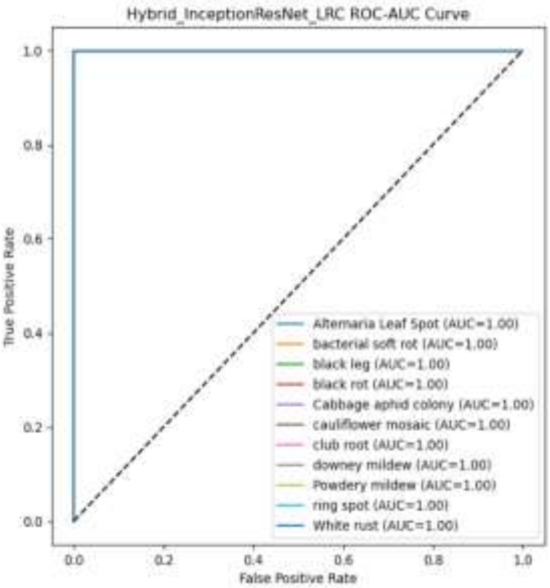


Fig. 4: Obtained ROC-AUC curve of IRNCNN

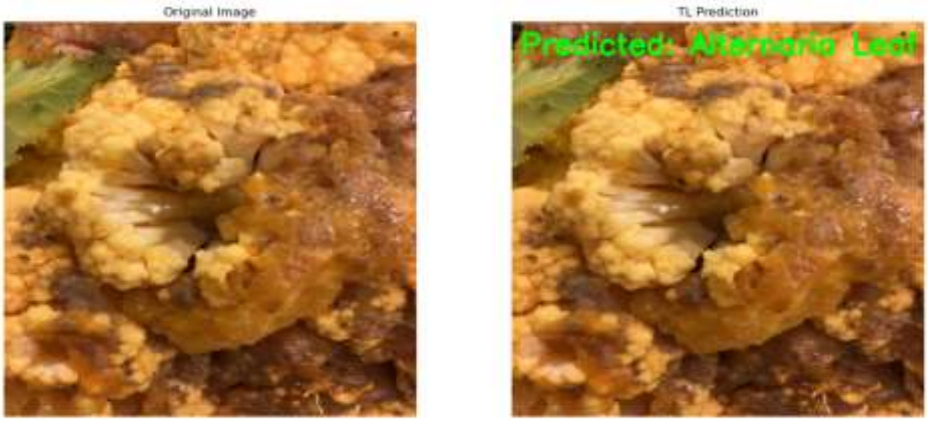
Fig. 5 illustrates the system performing inference on individual cauliflower leaf images, demonstrating the effectiveness of the IRNCNN model in real-time disease classification. The input images undergo preprocessing steps such as resizing, normalization, and feature enhancement to ensure consistency and improve feature extraction. The model leverages deep hierarchical representations to capture both low-level texture patterns and high-level semantic features. This enables accurate identification of subtle variations in color, structure, and lesion patterns across different disease classes. The results highlight the capability of the system to operate reliably on single-image inputs, making it suitable for practical field-level deployment.

(a)

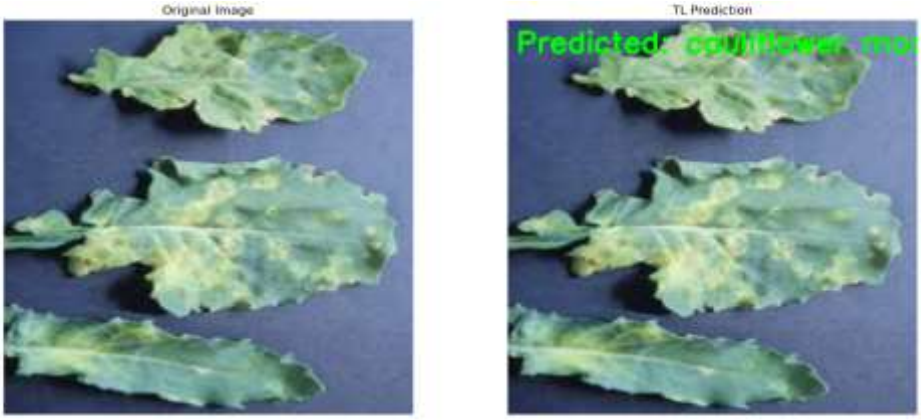
Fig. 5 (a) depicts the classification of bacterial soft rot, where the leaf exhibits clear symptoms such as tissue softening, water-soaked lesions, and irregular discoloration. The IRNCNN model effectively captures these visual characteristics and differentiates them from other disease patterns. The model focuses on localized regions with high moisture-related texture variations, leading to confident and accurate classification. The ability to detect such soft tissue degradation patterns demonstrates the model's sensitivity to bacterial infection features.

Fig. 5 (b) illustrates the detection of Alternaria leaf spot, characterized by small, dark circular lesions surrounded by yellow halos. The model extracts fine-grained textural and color-based features to identify these distinct spot patterns. It effectively distinguishes the concentric ring structures and surrounding chlorotic regions from other types of leaf damage. This indicates strong performance in recognizing fungal disease symptoms that involve complex visual patterns.

Fig. 5 (c) shows the classification of cauliflower mosaic, where the leaf presents mosaic-like discoloration and irregular vein patterns. The IRNCNN model captures both global and local variations in color distribution, enabling it to identify the characteristic patchy appearance. The hierarchical feature extraction mechanism allows the model to analyze vein distortion and uneven pigmentation simultaneously. This results in precise detection of viral infection symptoms that are often difficult to differentiate.



(b)



(c)

Fig. 5 (d) depicts the identification of cabbage aphid colony, where clusters of insects are visible on the leaf surface. The model successfully detects these aggregated patterns and distinguishes them from disease-induced lesions. By focusing on spatial grouping and structural irregularities, the IRNCNN model accurately classifies pest-related infestations. This demonstrates its capability to handle both disease and pest detection within a unified framework, enhancing its applicability in comprehensive plant health monitoring systems.

(d)

Fig. 5: Predictions on single test Image. (a) bacterial soft rot, (b) Alternaria Leaf Spot, (c) cauliflower mosaic, (d) Cabbage aphid colony.

Fig. 7 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.

Fig. 7: Predictions with Telegram Bot

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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