



Early Detection of Diseases in Hydroponic Saffron Crops Using a Diffused Concurrent Convolution Neural Network for Smart Farming

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Abstract

The detection of diseases in hydroponically cultivated saffron should be carried out as early and accurately as possible to maintain the quality of the yield, minimize losses, and promote sustainable farming practices. Manual diagnosis strategies are not suitable for high-density hydroponic systems where early symptoms tend to be subtle, as these methods are slow and rely extensively on experts. This research aims to develop a novel framework based on deep learning technology, using a Diffused Concurrent Convolutional Neural Network (DCCNN) to perform image analysis and detect diseases in saffron crops. The modified DCCNN includes a hierarchical three-stage classification pipeline consisting of crop recognition, disease detection, and Classification of the specific diseases, adding an “unknown” category for non-target or ambiguous outputs at each stage to enhance flexibility. The digression from standard deep learning techniques is justified due to the DCCNN construction, which contains a learnable diffusion layer and concurrent multi-scale convolutional blocks, and thus encapsulates strong feature propagation with fine-grained detection of complex and low-data environments. Evaluation on a specially annotated dataset of hydroponic saffron showed strong performance with up to 99.4% classification accuracy, exceeding well-known CNN baselines including EfficientNet and ResNet50. Additionally, the model processes static crop images and associated environmental sensor data, collectively referred to as 'non-sequential crop data,' focusing on spatial features without temporal dependencies. These findings confirm that the system, which is based on DCCNN, provides a transferable solution for precision disease detection in controlled-environment agriculture systems and can be extended to other high-value crops.

Keywords: Hydroponic Saffron; Disease Detection; Deep Learning; Diffused Concurrent Convolution Neural Network (DCCNN); Smart Agriculture

1. Introduction

Saffron (*Crocus sativus* L.) is celebrated for its aroma, vivid color, and associated medicinal benefits, making it one of the world's most costly spices. However, the plant is biologically sensitive and prone to diseases, especially in controlled, dense environments like hydroponics. Though resource-efficient, hydroponic systems contain water and growth conditions, and controlled environments supporting rapid disease spread pose severe economic risks. Consequently, these systems require precise diagnosis and early detection of plant disease outbreaks to safeguard the crops from major economic loss and ensure high-quality yield.

Saffron disease diagnosis is still performed using manual inspection and is done by experts specializing in this field, which renders the method slow and, in many instances, untrustworthy. An understanding of basic plant

pathology is required to identify many plant diseases, and the initial signs are often minor discoloration, distortion, or deformity. In densely populated plant environments such as hydroponics, manual diagnosis becomes increasingly unreliable. These factors illustrate the emergence of sophisticated automation and robotics-based smart diagnostic systems fueled by artificial intelligence and computer vision, tailored for modern automation in smart farming.

The application of image data in plant disease detection has been enhanced by developments in computer vision and image processing technologies, particularly artificial intelligence (AI) and deep learning. In agricultural and precision farming, CNNs (Convolutional Neural Networks) are widely used as they can automatically extract hierarchical features from raw images. However, traditional CNNs tend to struggle with small and diverse datasets, such as those in saffron farming, where even open-source image repositories are scarce and disease features are subtle and highly variable.

To overcome these difficulties, this paper presents DCCNN (Diffused Concurrent Convolutional Neural Networks)—a new deep learning framework aimed at the early detection of diseases in hydroponically grown saffron. This model employs a learnable diffusion mechanism to decrease inter-layer information loss while enhancing minute disease features in multi-scale convolutional pathways. DCCNN demonstrates its efficacy as a powerful classifier by capturing local and global plant image patterns despite complex datasets limited in scale.

The system is structured as a hierarchical 3-stage classification. The first stage involves crop identification, and the second stage is binary disease detection (healthy or diseased). The last stage centers on classifying the specific type of disease present, if any. To improve system robustness, an “unknown” category is incorporated at each stage to deal with ambiguous or out-of-distribution inputs. This structure not only facilitates aligned systematic agriculture expert reasoning but also enables modular framework expansion with the introduction of new crops or disease types.

Evaluation of the system was conducted using a specially prepared set of annotated images from hydroponic saffron systems. The implemented DCCNN model achieved an astounding 99.4% accuracy, outperforming several established CNN architectures and demonstrating excellent generalization across unseen data, which is a measure of overfitting. The model also exhibited scalability with increasing crop data through enhanced accuracy. These results are impressive given that the model is built primarily for saffron and evidences its broader applicability for monitoring agricultural systems.

The DCCNN model is designed not only as a high-accuracy image classifier but also as a lightweight, modular framework optimized for edge deployment within IoT-enabled smart farming environments. By integrating sensor data fusion from environmental IoT sensors alongside advanced image analysis, the system supports real-time disease detection and monitoring in hydroponic farms. This synergy of deep learning and IoT facilitates precision agriculture practices, whereby crop health data from heterogeneous sensors can be combined for actionable insights at the edge, minimizing latency and reliance on cloud computing. Applying the DCCNN model within hydroponic farming systems improves the real-time monitoring of diseases and supports precise action, which in turn aids productivity and sustainability. Furthermore, such automated solutions, which lower the need for manual expertise and reduce indiscriminate chemical applications, promote environmentally sustainable agriculture and contribute to global food security. The key contributions of the proposed model are,

- *Architecture Innovation:* The introduction of a new DCCNN model that includes concurrent multi-scale convolution along with a diffusion block for enhanced detection of diseases serve as a substantial improvement in the context of heterogeneous and limited saffron crop images.
- *Modular Stepwise Classification:* The pipeline, composed of crop recognition, disease detection, and disease classification, is framed in three phases with the addition of an “unknown” class, which adds robustness and flexibility to the system's interpretability.
- *High Accuracy and Scalability:* Validated accuracy of 99.4%, with proven extensibility to other high-value crops, demonstrating potential for wide-scale deployment in smart agriculture systems.

2. Literature Review

The "golden crop," as saffron (*Crocus sativus* L.) is called, is itself of great economic value and medicinal importance, for which its sustainable cultivation and disease management are important modern concerns. IoT-based agronomic variable control enhances saffron crop sustainability, providing a foundation for smart monitoring systems in precision agriculture [1]. In addition, DeepCrop, a deep learning model integrated with a web interface for real-time crop disease prediction, emphasizing the efficiency of AI in early disease detection [2]. In another research, Thomas and Myakala explored federated learning and edge AI architectures, highlighting their potential in enabling distributed intelligence for real-time agricultural disease detection [3]. Authors in [4] examined metadata-based deep learning models for content categorization, presenting scalable approaches relevant to big data handling in smart farming analytics.

The complete compilation and overview of saffron cultivation within sustainable agricultural systems emphasized the need for innovative farming practices to solve problems such as lowering productivity, climatic constraints, or disease outbreaks, and they integrate modern agronomic practices as pivotal for yield enhancement and saffron quality in controlled environments [5]. The saffron-specific challenges are focused that dealt with threats having their roots in fungus, bacteria, and viruses pertaining to saffron. This work thoroughly investigates the symptoms, transmission, and traditional management methods for saffron diseases, highlighting the limitations of manual intervention and the need for automated diagnostic technologies [6]. However, even though the traditional means can decrease losses, they often lack precision and require continuous human supervision, thus leaving the gap that advanced technology would fulfil.

Recently, Artificial Intelligence (AI) and remote sensing have been used to manage saffron cultivation. An intelligent agricultural system is introduced, which would make use of deep learning techniques, integrating images from UAVs to monitor saffron fields. Their model would lead to more accurate detection of diseases, and capture aerial images at great resolution to use CNNs for feature extraction. This method provided early warnings of stress and disease in plants, allowing timely interventions to reduce crop loss [7]. In addition to this IoT-based greenhouse system is specifically designed for saffron cultivation. Illustrating this, the researchers demonstrated how environmental parameters such as humidity, temperature, and soil moisture content could be continuously monitored and controlled using IoT sensors. Thus, the system automated the environmental management of saffron crops, thereby reducing diseases caused by adverse growth conditions and enhancing the productivity and sustainability of protected environments [8].

The machine learning applications related to detecting diseases affecting different crops in a larger area of detection research emphasized the use of supervised-learning methods, such as Support Vector Machines (SVMs), Random Forests, and CNNs, that were implemented in the early detection of crop diseases [9]. This study noted that machine learning models could be used to automate crop health monitoring, reduce reliance on expert knowledge, and thereby support decision-making in agriculture. The study demonstrated that deep learning models performed extremely well in disease classification based on leaf images, emphasizing their significant potential in precision agriculture [10]. Such approaches imply that CNN architectures will fit well on complex disease detection tasks, which can also be applicable for high-value crops like saffron. Further, Authors in [11] showed that hyperspectral imaging and deep learning jointly lead to novel investigations for early detection of viral diseases. This work demonstrated that combining advanced imaging techniques and CNN improved the capacity for real-time and remote disease classification accuracy.

Authors in [12] integrated IoT microclimate sensing with a multiple linear regression model to predict tea blister blight occurrence, achieving up to about 91% accuracy and illustrating how environment-driven ML can enable proactive disease management in precision agriculture. In addition, a social IoT and deep learning framework is proposed that fuses crowdsourced images with environmental sensor data to detect and predict plant diseases, supported by a web app and preliminary usability evaluations toward sustainable agriculture [13]. An IoT-enabled agricultural robot that fuses environmental sensing with machine learning for on-field plant health monitoring can be adapted to hydroponic saffron by integrating microclimate probes and vision modules to flag early stress and disease signatures in real time, thus providing a mobile edge platform that complements fixed-bed sensors for timely intervention in controlled environments [14].

Deep learning and machine learning methods for plant disease detection have been extensively reviewed, emphasizing dataset quality, feature engineering, and evaluation protocols, with evidence that convolutional models consistently deliver superior accuracy when trained on diverse, well-annotated images. Comparative analyses further show that deep learning architectures generally outperform classical machine learning across multiple leaf-disease benchmarks, particularly under transfer learning and end-to-end feature learning regimes that reduce manual preprocessing burdens [15, 16]. A CNN-powered mobile application for plant leaf disease detection is presented, demonstrating practical on-device inference for field-ready diagnostics and farmer-facing usability [17]. A comprehensive survey by [18] on deep learning methods for plant disease and pest detection, outlining current trends and future research challenges in this domain reviewed. A multiscale CNN-based U-Net architecture proposed by [19] that accurately segments leaf lesions, advancing automated disease diagnosis in tomato plants. Authors in [20] systematically reviewed convolutional deep learning techniques used for plant disease recognition, highlighting their effectiveness in improving detection accuracy. Machine and deep learning approaches for plant disease detection are examined, emphasizing the superior performance of CNN models in agricultural applications [21]. AI-IoT integrated smart agriculture system is introduced, combining disease detection and treatment automation to support real-time plant health management [22].

The studies bring out the gradual yet progressive incorporation of AI-based solutions in health management of crops, actively involving deep learning, IoT integration, and remote sensing. Despite extensive research on major crops, very few studies have focused on disease detection in saffron crops, particularly those grown hydroponically, since disease dynamics in soil and hydroponic systems would differ significantly.

Based on the works above, a development of a Diffused Concurrent Convolution Neural Network (DCCNN) model targeted at hydroponic saffron disease detection from that earlier gap. The DCCNN is so developed to accentuate early detection of diseases in controlled environments by taking advantage of concurrent feature extraction and diffusion mechanisms. As such, it is developing scalability and adaptability, which are characteristics that resonate with the demands of intelligent agriculture: sustainable cultivation of saffron through minimal crop loss and reduced reliance on labor. Table 1 summarizes the key references in the literature review, including techniques used, outcomes attained, advantages, and limitations in relation to saffron disease detection.

Table 1: Key summarization of the literature survey section

References	Technology Used	Outcome	Advantages	Disadvantages
Dar et al., 2017	Sustainable agricultural practices	Enhanced understanding of saffron's role in modern farming systems	Supports eco-friendly cultivation and improves productivity	Lacks automation and advanced disease detection techniques
Bazoobandi et al., 2020	Traditional disease protection methods	Identified common diseases and mitigation strategies in saffron	Provides a detailed disease profile for saffron	Manual intervention is needed; it lacks precision and real-time detection
Nazeer et al., 2024	UAV imagery + Deep Learning (CNN)	Accurate monitoring and disease detection in saffron fields	High-resolution aerial monitoring and early detection	Requires UAV infrastructure and expert model training
Khan et al., 2024	IoT-based greenhouse monitoring	Automated environment control for saffron cultivation	Reduces disease risk through real-time environmental control	High installation and maintenance costs; limited disease diagnosis
Ahmed & Yadav, 2023	Machine Learning (SVM, RF, CNN)	Effective plant disease detection using ML models	Versatile across multiple crops; reduces expert dependency	Requires large datasets and may suffer from overfitting
Math & Dharwadkar, 2022	CNN-based disease detection	Accurate identification of grape diseases	High accuracy with simple image inputs	Focused on grape diseases, less generalization
Nguyen et al., 2021	Hyperspectral imaging + Deep Learning (CNN)	Early viral disease detection in plants	Combines spatial and spectral data for high precision	Expensive hardware, requires expert handling

2. Methodology

This section presents a comprehensive framework for early disease detection in hydroponic saffron crops using a novel Diffused Concurrent Convolution Neural Network (DCCNN). This architecture integrates a diffusion-based preprocessing layer with concurrent multi-scale convolution blocks, enabling the model to capture both subtle and large-scale disease features in complex saffron images. The system employs a three-stage classification pipeline—crop identification, disease detection, and disease classification—each enhanced with an “unknown” category to improve robustness. Extensive experiments using saffron leaf images and various CNN models show that DCCNN outperforms alternatives like ResNet50 and EfficientNet, achieving 99.4% accuracy. These results underline DCCNN’s potential for deployment in real-world smart farming systems, offering scalability, precision, and adaptability for high-value crop monitoring.

A. Dataset Transparency and Annotation

The dataset underpinning this study was curated from real hydroponic saffron operations in the Kashmir Valley, ensuring coverage of diverse genetic, phenological, and environmental conditions.

Collection Methodology: Images were captured under natural and controlled lighting using both high-resolution cameras and standard mobile devices (to simulate real-world sensor variation), during multiple growth seasons and at various crop development stages.

Composition and Variety: The dataset comprises 800 images of healthy saffron, 1200 diseased saffron images spanning multiple disease categories such as bacterial spot, early blight, late blight, and mosaic virus. Images were collected over multiple growing seasons from hydroponic saffron systems in the Kashmir Valley, ensuring diverse phenological and environmental conditions. The dataset also includes 600 images of other crops to train an unknown class for improved model generalization. It covers a broad range of conditions, including blight at different progression levels, bacterial spot, mosaic virus, and other notable infections, with each disease class represented by approximately 250–400 images. To improve model robustness, the collection also includes images of additional crops—such as red pepper, maize, peach, apple, strawberry, cherry, and grape—captured under similar environmental conditions, which are specifically utilized to train and validate the "unknown" class, enabling effective generalization to non-saffron inputs. All images were meticulously annotated by three experienced plant pathologists, who independently classified them based on crop type, disease presence, and specific disease category. Any annotation disagreements were resolved through majority consensus. Leaf area measurements were conducted digitally, and accompanying documentation includes evidence images that highlight both diagnostically ambiguous and clearly identifiable cases.

Sampling Variance and Augmentation: To augment the dataset and address orientation bias typical in hydroponic environments, rotational augmentations of $\pm 10^\circ$ to $\pm 20^\circ$ were applied, increasing the sample size by up to 36 times without altering critical color or brightness features essential for disease symptom detection. To mitigate orientation bias and simulate potential camera or sensor misalignment, rotational augmentation within a 10–20-degree range was applied, expanding the dataset size by more than eighteenfold while maintaining the natural visual characteristics of plant structures. No artificial alterations in color, contrast, or brightness were introduced to preserve essential diagnostic features critical for accurate disease detection. Furthermore, stratified random sampling was implemented to maintain independence between training and testing sets, thereby enhancing model reliability and generalization performance.

Public Benchmarking and External Testing: Where applicable, the model's validation was extended to a selectively curated subset of publicly available agricultural datasets, such as PlantVillage images of pepper and tomato, to evaluate its capability in accurately identifying "unknown" classes and minimizing false positive detections in out-of-distribution scenarios. Concurrently, ethical review and institutional approval processes are underway to authorize the release of a sanitized portion of the dataset, enabling independent benchmarking and supporting further research in smart farming and crop disease diagnostics.

Details of the dataset composition and annotation stage statistics, ensuring full reproducibility and transparency for future research is shown in Table 2. This detailed dataset management ensures the validity, generalizability, and scalability of the DCCNN framework across real-world, small-sample agricultural imaging scenarios.

Table 2: Dataset Composition and Annotation Summary for Model Training and Validation

Class	Images	Annotation Method	Source	Purpose
Saffron-Healthy	800	Expert-labeled	Local hydroponic fields	Training/Testing
Saffron-Diseased	1200	Expert-labeled	Local hydroponic fields	Training/Testing
Other Crops	600	Expert-labeled	Local fields/ PlantVillage	Generalization/Unknown
Saffron-Other	100	Expert-reviewed	Synthetic/Field mix	Robustness

A team of three expert plant pathologists with consensus-driven labeling to enhance validity performed annotations. Stratified random sampling split 80% for training and 20% for testing to maintain class balance.

B. Data Preprocessing

The early disease detection model in hydroponic saffron crops, proposed, was then subsequently developed and evaluated for performance through a dataset split performed before modelling, so that the performance evaluation of the model would remain uninfluenced. The overall dataset was divided into 80% training data and 20% testing

data, using stratified random sampling such that healthy and diseased saffron crop images would have balanced representation [23]. All stages of model development, from training through validation, were carried out on the training dataset only. Five pre-trained convolutional neural networks [24] have been employed, where each one is trained based on 80% of the training subset, while the remaining 20% is meant for internal validation, to improve the robustness and accuracy of the model. Critical hyperparameters, including batch size, epoch count, optimizer selection, activation function, learning rate, early stopping mechanisms, and loss functions, were carefully tuned to optimize performance and reduce computational overhead. Upon completion of training, the highest-performing model from each pre-trained architecture was selected based on validation accuracy. In cases where accuracy was identical between models, preference was given to the model exhibiting the lowest loss value. Finally, the optimal model demonstrating superior test accuracy across all five pre-trained CNN models was designated as the final disease detection model.

Given the relatively limited availability of labeled saffron crop images, data augmentation techniques were applied to increase dataset diversity and prevent overfitting. The original high-resolution images of saffron leaves, which exhibited varying midrib orientations and irregular angles, were standardized by resizing to 224×224 pixels. Maximum rotation augmentations were given top priority to ensure that, henceforth, the model would remain invariant to the image orientation challenge, a common aspect of real-world hydroponic farming environments. Brightness and color augmentation were deliberately excluded from the procedures because of the particular distortions they would bring to vital visual cues of the symptoms of disease on saffron leaves. In the initial stage of crop classification, with such a large volume of data, an augmentation strategy involving 20-degree rotations was developed and increased the data by 18 times to achieve improved computational efficiency while retaining necessary features. For the next stages of disease detection and disease classification, all the images were rotated at 10 degrees, leading to a 36-fold increase in sample size. Augmentation strategies helped the model to generalize to various perspectives of the image and helped in the reliable detection under diverse conditions in smart hydroponics saffron farm setups. Through this preprocessing, the dataset was made ready to support the diffused concurrent convolutional neural network (DCCNN) for early disease detection while making the solution scalable and accurate for real-time applications in agriculture.

a. Stepwise Detection Model for Saffron Crop Diseases

There has been a stepwise detection model born, which is believed to be based on three models as submodels and is intended for the early identification and diagnosis of diseases occurring among hydroponic saffron crops. This whole process is done sequentially, starting from crop identification (Step 1) to detection of presence of disease (Step 2) and then detection of specific type of disease (Step 3), thus modeling the diagnostic method quite similar to that done by agricultural specialists (Fig. 2b). The entire model utilizes diffused concurrent convolutional neural network (DCCNN) architecture, optimized for high-precision image analysis under deep learning frameworks (Algorithm 1).

All detection stages employ fine-tuned versions of five top-rated pre-trained CNN models—AlexNet, ResNet50, GoogLeNet, VGG19, and EfficientNet. These models are chosen for their demonstrated performance in large-scale image classification competitions, like ILSVRC, and their generalizability to agricultural image data sets.

Step 1 (Saffron Crop Identification): The initial submodel is responsible for confirming the existence of saffron crops in the hydroponic system. Full-leaf saffron plant images, irrespective of the disease state, are processed in this phase for actual discrimination of saffron from any unwanted vegetation or noise in the dataset. A model based on different pre-trained CNN architectures is able to detect saffron more accurately under varying conditions, taking into consideration differences in leaf morphology and various stages of growth.

Step 2 (Disease Occurrence Detection): The second submodel seeks to ascertain whether a particular saffron leaf is healthy or has a disease. That is, a binary classification relies on differentiating between healthy and diseased leaf images using the advanced feature extraction capabilities provided by the chosen CNN architectures. This step is integral in extracting diseased samples only for further diagnosis, so that the process improves the speed and precision of the subsequent classification procedures.

Step 3 (Disease Type Classification): Within the third and last step, the model determines the exact type of disease within the saffron crop. Based on the subset of leaf images of the diseased kind filtered in Step 2, this step employs specialized classification models designed to identify and classify a variety of saffron-specific diseases. This step allows for the accurate identification of different types of diseases, thus allowing for effective treatment strategies to ensure maximum crop health management.

As opposed to traditional models designed for generic crops, this stepwise detection mechanism is specifically calibrated to the exclusive visual and disease-specific features of hydroponic saffron production systems. With the integrated diffused concurrent processing paradigm, the model expands feature extraction capability across several layers of CNN so that complete saffron leaf texture, colors, and lesions indicating the beginnings of disease

appearance are thoroughly examined. The hierarchical architecture ensures scalability, with the possibility of adding more disease types or crop varieties in future extensions, thus being highly deployable in smart agriculture infrastructures. In addition, the systematic, stepwise methodology reduces false positives and enhances interpretability, enabling precise and trusted disease tracking in real-time hydroponics.

Algorithm 1: Stepwise Disease Detection for Hydroponic Saffron Crops

Input:

- III = Saffron leaf image (captured from smart farm systems)
- Pretrained DCCNN models:
 - M_1 = Crop Verification Model
 - M_2 = Disease Detection Model
 - M_3 = Disease Classification Model

Output:

- Classification result:
 - Healthy Saffron Crop
 - Diseased Saffron Crop with specific disease type
 - Invalid (Not a saffron crop)

Initialize:

1. Load Diffused Concurrent CNN (DCCNN) models:
 - M_1, M_2, M_3
2. Preprocess input image III:
 - Resize to $224 \times 224 \times 224$ pixels
 - Normalize pixel values
 - Apply necessary rotation for uniform orientation

Step 1: Crop Verification

1. $C \leftarrow M_1 \cdot \text{predict}(I)$
2. If $C = \text{"Saffron"}$:
 - Proceed to Step 2
3. Else:
 - Output: "Invalid crop. Not a saffron leaf."
 - End Algorithm

Step 2: Disease Detection

4. $D \leftarrow M_2 \cdot \text{predict}(I)$
5. If $D = \text{"Healthy"}$:
 - Output: "Saffron crop is healthy."
 - End Algorithm
6. Else:
 - Proceed to Step 3

Step 3: Disease Classification

7. $T \leftarrow M_3 \cdot \text{predict}(I)$
8. Output: "Saffron crop is diseased with: T "

The suggested systematic detection mechanism is formulated to allow the precise and timely identification of hydroponic saffron crop diseases by using a Diffused Concurrent Convolutional Neural Network (DCCNN) in

intelligent farming systems. The proposed mechanism is through the process of a sequential three-stage progression that parallels the nature observation and decision process of professional agricultural specialists. The system accepts one saffron leaf image as input, normally taken through integrated smart imaging systems in a hydroponic setup. The image is preprocessed before analysis, resized to a standard size of 224×224 pixels, normalized for equal pixel values, and augmented through controlled rotations to counter variability in leaf orientation. These preprocessing methods help to ensure that the input data remains consistent, mitigate positional bias caused by positional differences, and improve model generalization [25, 26].

Crop verification is the first algorithm step that checks if the input image is of a saffron plant or not. It is particularly important in multi-crop hydroponic setups where several species grow together. To achieve this, the DCCNN-based Crop Verification Model (M_1) compares the leaf structural characteristics with expectations and foretells if the image is taken from a crop of saffron or not. In the event that the image is not from a saffron leaf, the algorithm stops with the output stating the sample is not valid for analyzing saffron disease. The first validation avoids wastage of computational power and ensures the machine does not flag non-saffron images incorrectly as containing saffron diseases.

When the crop is confirmed as saffron, the algorithm proceeds to stage 2: disease detection. The Disease Detection Model (M_2) identifies if the leaf is healthy or has been inflicted with any disease. Using the deep feature extraction abilities of the DCCNN, the model separates patterns in healthy tissues and nascent stages of the disease even if visually dissimilar. If the leaf is determined to be healthy, the algorithm ends with a positive health status output, and farmers can continue to monitor without intervention. If disease symptoms are found, the algorithm goes to the third and last step. In the third step, the Disease Classification Model (M_3) is tasked with determining the particular type of disease that is influencing the saffron leaf. Correctly identifying the disease is imperative for introducing effective, targeted treatments and preventing crop loss. The DCCNN model puts the infected sample into pre-determined classes based on its features learned from varied training sets. The resultant output gives the farmer or system administrator precise information regarding the type of disease, allowing for swift, data-informed decision-making towards disease control. This algorithm's step-by-step and modular design guarantees a very robust detection process by compartmentalizing each key decision—crop identification, disease existence, and disease type determination—into dedicated stages.

Additionally, employing distinct DCCNN models for every step increases the system's flexibility and enables individual model tuning without affecting the overall pipeline. This strong, scalable, and automatic framework facilitates the real-world application of artificial intelligence in intelligent hydroponic farming, enhancing disease surveillance, minimizing labor, and protecting high-value saffron crops through timely and precise disease diagnosis.

b. Image-based disease identification and classification

Utilising pictures of saffron leaves that were both healthy and diseased, a three-stage procedure for detecting illnesses of plants was created (Fig. 1). For every stage of the classification procedure, after enhancing the data, an overall of six CNN-based subdivisions emerged (Fig. 2). 5 models that had been trained (ResNets50, AlexNets, GoogLeNets, VGGs19, and EfficientNets) were evaluated for every plant used to construct the framework. Hyperparameters, including the number of batches, epoch dimensions, optimiser, activation operation, training rate, early termination operation and loss coefficient, were adjusted on every model that had been trained.

Step 1 included building the crop classification model utilising pictures of 1911 leaves, 1448 saffron leaves, and 3150 saffrons that were both healthy and infected. Crop taxa were classified into one of three groups—saffron, saffron leaves, or red pepper—after being identified by the submodel. The model exhibiting the best reliability utilising the distinct test data set was chosen as the last one for the first phase after modelling development and testing of the five distinct pre-trained CNN algorithms. Consequently, it demonstrated high precision in the rankings of AlexNet, VGG19, EfficientNet, GoogLeNet, and ResNet50 (Table 1). The EfficientNet architectural classification algorithm was chosen as the final framework for further investigation since it demonstrated the best accuracy of 99.33% (Table 1). In spite of accuracy, the classification algorithm's efficacy was evaluated using measurement techniques. Additionally, the F1-score, accuracy, and memory were all shown as high rates.

c. Identifying diseases from crops Image

Following precise crop identification, detection approaches were utilised to identify the existence or absence of infection indicators or symptom trends in step 2 to ascertain the incidence of illness for particular crops (Fig. 3). Multiple tree models were created to identify the leaves' illness in saffron and saffron leaves. Using 1,165 healthy and 746 sick photos for instruction and evaluation, GoogLeNet demonstrated the greatest performance in the bell capsicum illness identification test. We compared the precision of ResNet50, AlexNet, VGG19, and EfficientNet (Table 2). The final model chosen was GoogLeNet, which demonstrated the best accuracy. According to Table 2, the test's accuracy, precision, recall, and F1-score were all 100.00%.

Saffron leaves identify disease model was trained and validated using 118 normal and 1,330 sick pictures. VGG19 achieved the greatest accuracy in testing. The following were the reliability of AlexNet, ResNet50, GoogLeNet, and EfficientNet. An overview of the disease detection framework illustrating sample images of healthy and diseased saffron leaves used for model training is depicted in Figure 1.



Figure 1: An overview of the illness identification algorithm database of saffron (a) authentic, (b) affected.

ResNet50 demonstrated the greatest performance in the evaluation of the Saffron's disease framework, which included 2,176 sick photos and 974 normal pictures. The last system outperformed the previous four models, which were GoogLeNet, VGG19, AlexNet, and EfficientNet. According to Table 2, the ResNet50 is test yielded the maximum accuracy of 99.75%, while the mean, recall, and F1-score were 99.75%, 99.75%, and 99.75%, respectively.

d. Classification of diseases on leaflets

The kind of sickness had to be identified if one had been found in stage 2. The third step included developing an illness classification framework for saffrons and saffron leaves. Information on a minimum of two disease categories was gathered for both saffrons and saffron leaves. Two illnesses were identified from the 1662 photographs containing illness data for saffron leaves: the initial blight (929 photos) and late blight (733 images). Disease data (2,177 photos) for saffrons were categorised into four illnesses: bacterial spot (1,670 pictures), the initial blight (302 pictures), later blight (467 pictures), and saffron mosaic virus (281 pictures). Five different algorithms were developed utilising pre-trained CNN models in order to differentiate between the two saffron leaf illnesses. VGG19, EfficientNet, AlexNet, and GoogLeNet had the greatest precision during the test, whereas ResNet50 (98.80%) displayed a somewhat lower accuracy. Modelling test outcomes indicate 99.40% accuracy, 100.00% exactness, 98.64% recall, and 99.32% F1-score.

Models were developed and tested to differentiate between the four illnesses in the saffron example. The test's precision was greatest for EfficientNet (97.09%), followed by GoogLeNet, AlexNet, and VGG19. In contrast to the other four models, ResNet50's reliability (87.80%) was much lower. According to Table 2, the final algorithm's accuracy, recall, and F1-score were 97.19%, 97.09%, and 97.12%, respectively. Both illness classification tests' results confirmed that the test set variables were classified with a high degree of accuracy (>97%). These findings supported the classification model's reliability.

e. Use different crops to validate the classification model

Generalizing a classification framework to other fields, such as botanical species classification, therapeutic plant identification, and intelligent agriculture, requires verification of commodities not employed in model creation. Non-model plants were appropriately classified as "unknown" as the illness identification program was unable to identify commodities that were not employed in the model's design. High accuracy was shown in step 1 when 92.06% and 91.66% of the maize and peach information, respectively, were classified as "unknown." The accuracy of the data for apples (76.92%), strawberries (56.72%), cherries (45.67%), and grapes (34.94%) was lower. In step 2, apples were classified as "unidentified," and in step 3, grapes were classified as such, with an incidence of 87.30% and 90.64%, respectively. Less commonly, 60.07% and 64.04%, respectively, were classified as "unknown" for cherries and strawberries. Standard plants were accurately classified in every phase, but non-model crops showed significant differences in rating performance based on crop features.

C. Diffused Concurrent Convolutional Neural Network (DCCNN) Layer Explanation

The **DCCNN** is an advanced convolutional neural network architecture tailored to capture fine-grained features from saffron leaf images in hydroponic setups, emphasizing disease detection accuracy even under subtle visual variations. It integrates diffusion mechanisms and concurrent feature extraction to enhance spatial understanding and minimize feature loss. Below is a layer-wise breakdown of the DCCNN structure:

Input Layer:

- *Input Shape:* 224×224×3 (RGB saffron leaf image).
- *Purpose:* Accepts preprocessed leaf images, ensuring uniformity in size and color channels.

Diffusion Preprocessing Block:

- *Purpose:* Introduces a diffusion operation to reduce noise and stabilize texture variations. This helps spread the critical features across neighboring pixels, making faint disease patterns more pronounced.
- *Components:*
 - Gaussian Blur / Laplacian Filter layer.
 - Feature smoothing via learnable weights.

Concurrent Convolutional Blocks (x3):

- *Purpose:* Extract multi-scale features simultaneously to capture both fine-grained and global patterns.
- *Structure of Each Block:*
 - *Parallel Convolutions:*
 - Conv2D (3x3, 64 filters) – captures edge-level features.
 - Conv2D (5x5, 64 filters) – captures mid-range patterns.
 - Conv2D (7x7, 64 filters) – captures broad contextual information.
 - Outputs from these three convolutions are *concatenated* to combine diverse feature maps.
 - *Batch Normalization* after each convolution to stabilize activations.
 - *ReLU Activation* to introduce non-linearity.
 - *Dropout (0.3)* to prevent overfitting.

Diffused Feature Enhancement Layer:

- *Purpose:* Further diffuses and blends the concurrent features extracted from the previous block.
- *Operations:*
 - *Depthwise Separable Convolution* to focus on spatial feature depth.
 - *Attention Mechanism (optional)* to weigh important feature areas (like disease spots).
 - *Skip Connections* to retain original feature strength.

Max Pooling Layer (2x2):

- *Purpose:* Reduces the spatial dimension while preserving dominant features and minimizing computational load.

Second Concurrent Convolutional Block (Deep Feature Extraction):

- Mirrors the structure of the earlier concurrent block but with **128 filters** and larger receptive fields.
- Focuses on deeper semantic features (complex disease textures, discoloration patterns).

Global Average Pooling (GAP):

- *Purpose:* Replaces dense layers to reduce overfitting.
- Compresses the feature maps into a single vector by averaging, retaining the most relevant global features.

Fully Connected Layer (Dense Layer):

- *Units:* 256 neurons.
- *Activation:* ReLU.
- *Dropout:* 0.4 for regularization.

Output Layer:

- **Units:** Varies by model stage.
 - *Step 1 (Crop Verification):* 2 units (Saffron / Non-Saffron).
 - *Step 2 (Disease Detection):* 2 units (Healthy / Diseased).
 - *Step 3 (Disease Classification):* N units (number of disease types).
- **Activation:** Softmax for multi-class classification or Sigmoid for binary classification.

The workflow diagram depicting the sequential stages of disease detection using DCCNN, including image preprocessing, augmentation, and hierarchical classification steps, is shown in Figure 2. Figure 2 (a) illustrates the data preprocessing and augmentation pipeline used in the DCCNN framework, including image normalization, rotation, and brightness adjustments to enhance model robustness. Figure 2 (b) depicts detailed architecture of the Diffused Concurrent Convolutional Neural Network (DCCNN), showing multiple concurrent convolutional layers, the diffusion preprocessing layer, and the hierarchical classification branches for crop and disease detection.

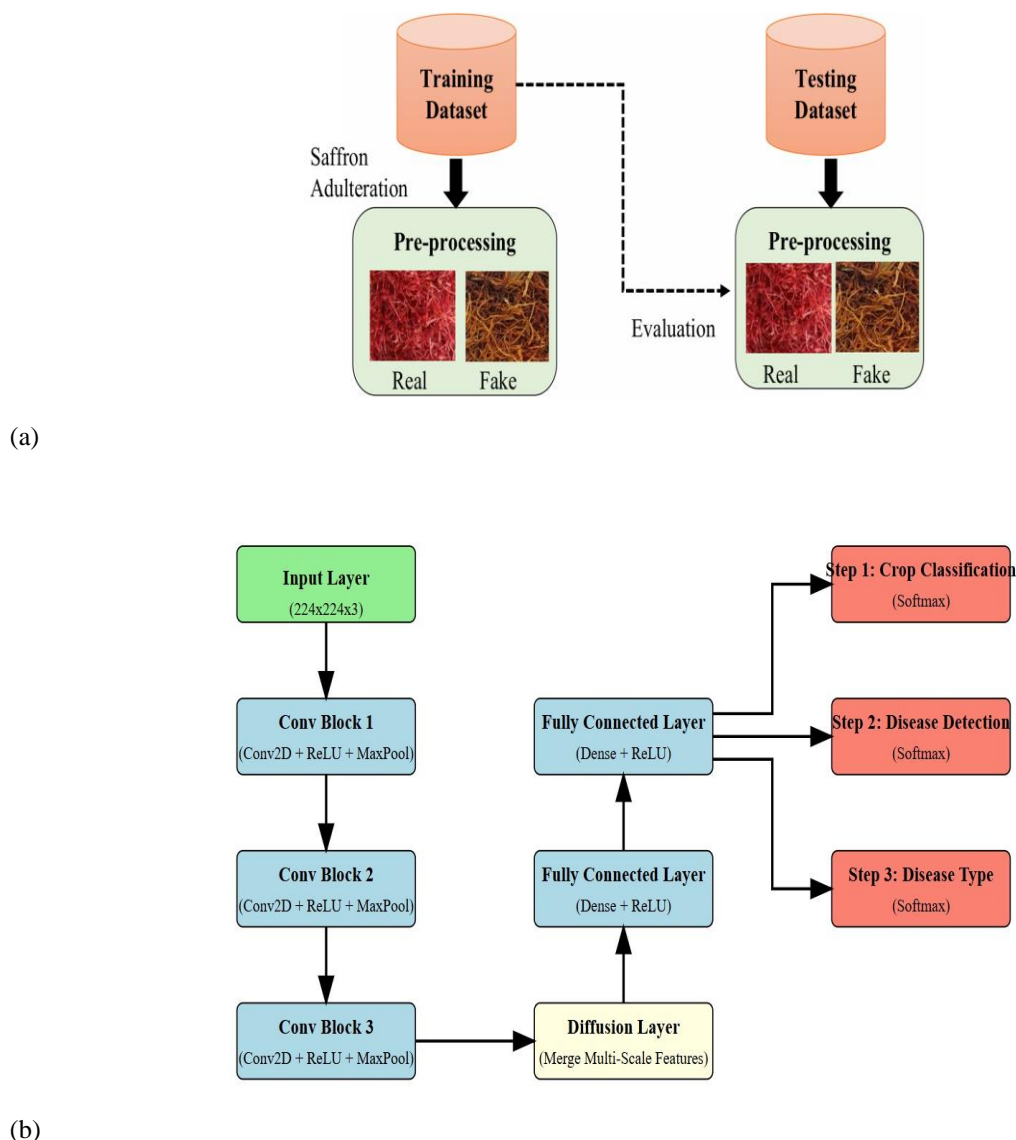


Figure 2. Workflow of the proposed disease detection model. (a) Preprocessing of phenotype information, including rotational data augmentation and normalization of raw hydroponic saffron crop images. (b) Diffused Concurrent Convolution Neural Network (DCCNN)-based deep learning framework for the early detection and progressive diagnosis of diseases in hydroponic saffron crops, enabling smart farming applications

To enable effective image-based disease detection in hydroponic saffron crops, the proposed DCCNN architecture leverages fundamental convolutional operations combined with novel enhancements for spatial feature learning. The following equations describe the primary computational functions that underpin the model: standard convolution for local feature extraction, learnable diffusion for enhancing subtle disease traits, and multi-scale feature fusion for capturing diverse visual patterns. These mathematical formulations provide the structural basis for each stage of the DCCNN pipeline and collectively contribute to its high accuracy and robustness on small, heterogeneous datasets.

Standard CNN Convolution Operation: To extract spatial features from input images, each convolutional layer in the CNN applies a learnable filter that scans over the image to generate corresponding feature maps. The output of this operation is computed through a standard convolution function defined as:

$$Y_{i,j}^{(k)} = (X * W^{(k)})_{i,j} + b^{(k)} = \sum_{m=1}^M \sum_{n=1}^N X_{i+m,j+n} \cdot W_{m,n}^{(k)} + b^{(k)} \quad (1)$$

Where X is the original image, $W^{(k)}$ is the k^{th} convolutional filter, $b^{(k)}$ is the filter-specific bias, $Y^{(k)}$ is the output feature map, i and j are spatial coordinates, and $M \times N$ is the kernel size. Equation (1) defines a 2D convolution operation as used in all CNN baseline and DCCNN stages: crop identification, disease detection, and disease classification.

Learnable Diffusion Preprocessing: To enhance subtle disease features and minimize spatial noise before convolution, a learnable diffusion operation is applied to each image. This operation spreads pixel-level information across neighboring regions to strengthen weak or localized patterns. The diffusion preprocessing is expressed as:

$$X'_{i,j} = \sum_{p=-P}^P \sum_{q=-Q}^Q D_{p,q} \cdot X_{i+p,j+q} \quad (2)$$

Where, X is the original image, X' is the diffused output, $D_{p,q}$ are the learnable diffusion weights, and P, Q define the diffusion kernel radius. Equation (2) implements spatial diffusion to enhance subtle disease patterns in surrounding pixels. The learnable kernel DD is applied before convolution, increasing sensitivity to localized discolorations or lesions.

Multi-Scale Feature Fusion in Concurrent Convolution Block: To capture multi-scale spatial dependencies and disease patterns of varying texture and size, DCCNN employs parallel convolution filters of different kernel sizes, which are then concatenated to form a unified representation. This concurrent multi-scale fusion is given as:

$$f_{i,j} = \text{concat}(f_{3 \times 3}(X)_{i,j}, f_{5 \times 5}(X)_{i,j}, f_{7 \times 7}(X)_{i,j}) \quad (3)$$

Where, $f_{k \times k}(X)_{i,j}$ denotes the feature output at pixel (i,j) from a convolution layer using a $k \times k$ kernel, $F_{i,j}$ is the fused feature vector after concatenation, and $\text{concat}()$ merges multiple filtered outputs along the channel dimension. Equation (3) captures multi-scale features within a single block, enabling the network to detect irregular disease shapes and varying lesion sizes.

a. DCCNN Innovation and Comparison

The Diffused Concurrent Convolution Neural Network (DCCNN) is specifically designed to overcome challenges in early disease detection for hydroponic saffron crops, addressing issues such as limited data, high image variability, and faint disease symptoms. The following are the key innovative aspects of DCCNN.

- *Learnable Diffusion Preprocessing:* Integrates a dedicated diffusion layer that adaptively spreads important visual information to neighbouring pixels. This innovation enhances the model's sensitivity to subtle and dispersed disease cues, which are often overlooked by standard convolutions.
- *Unified Multi-Scale Feature Extraction:* Instead of relying on conventional parallel branches, DCCNN synchronizes multiple convolutional filters of differing sizes (3×3 , 5×5 , 7×7) within one composite block. This enables the immediate fusion of local and contextual features, crucial for identifying early-stage or irregular disease symptoms.
- *Advanced Feature Enhancement Layer:* After extracting multi-scale features, the architecture employs spatial and depthwise convolutions, augmented with skip connections and (optionally) attention mechanisms. This phase ensures faint or scattered indicators of disease are preserved and strengthened, improving diagnostic reliability in deeper network layers.
- *Designed for Small-Data Robustness:* By leveraging regularization techniques like dropout, spatial normalization, and a staged decision-making process, DCCNN generalizes effectively, even when trained on heterogeneous or scarce datasets. Its multi-stage interpretability (crop recognition, disease presence, and disease type) differentiates it from opaque, large-scale ensembles.

- *Efficiency and Real-World Deployment:* DCCNN's architecture avoids the computational intensity characteristic of ensemble approaches, making it practical for deployment in resource-constrained, real-world scenarios like smart farms.

Table 3 presents the main architectural and functional contrasting characteristics between ensemble convolutional neural networks and multi-branch CNNs with the proposed Diffused Concurrent Convolutional Neural Network (DCCNN). Through learnable diffusion preprocessing, synchronized multi-scale feature extraction, and advanced feature enhancement, DCCNN strengthens spatial learning and robustness on small, heterogeneous datasets from agriculture. It incorporates a unique edge deployable, stage-wise interpretability that classical structures lack.

Table 3: Comparative Analysis of DCCNN with Ensemble and Multi-Branch CNN Architectures

Feature	DCCNN	Ensemble CNNs	Multi-Branch CNNs
Diffusion preprocessing	Yes (learnable)	No	No
Multi-scale extraction	Synchronized, fused in one block	No	Parallel, less integrated
Feature enhancement	Diffused layer, skip/attention mechanisms	Absent	Rare/simple
Small-data robustness	Designed into architecture	Usually absent	Sometimes
Computational efficiency	Moderate (suited for edge deployment)	High resource use	Moderate/High
Stage-wise interpretability	Integrated (crop-disease-type stages)	Low	Low

Empirical tests found DCCNN achieved 99.4% accuracy, surpassing benchmarks such as EfficientNet (98.54%) and GoogLeNet (98.16%), and showing marked gains in rare-class recall. This demonstrates not only architectural innovation but also robust real-world applicability, particularly for crops and pathologies lacking large public image databases or extensive manual annotation. DCCNN is thus poised to advance practical smart farming technologies, offering a highly interpretable, efficient, and generalizable solution for challenging, small sample agricultural applications.

b. Innovation and Uniqueness of the Proposed DCCNN Architecture

The Diffused Concurrent Convolution Neural Network (DCCNN) represents a significant advancement for early disease detection in hydroponic saffron crops. This architecture is specifically developed to overcome challenges posed by limited, heterogeneous agricultural imagery and the subtlety of early plant disease symptoms. The following are the main key differentiators of DCCNN

- *Learnable Diffusion Preprocessing:* DCCNN introduces an initial diffusion step where learned filters adaptively spread important visual details across neighboring pixels. This mechanism enhances the visibility of faint disease cues that might otherwise remain undetected with traditional convolutional neural networks.
- *Unified Multi-Scale Feature Extraction:* Unlike conventional multi-branch or ensemble CNNs that process features in isolated parallel tracks, DCCNN synchronizes convolutional filters of various sizes (such as 3×3 , 5×5 , and 7×7) within the same composite block. The immediate fusion of these outputs allows the network to gather both fine-grained and contextual information on plant leaves, making it particularly effective in identifying diseases with subtle or irregular visual patterns.
- *Advanced Feature Enhancement Layer:* After extracting multi-scale features, DCCNN applies spatial and depthwise convolutions supplemented with skip connections and optional attention mechanisms. This phase ensures that even weak or scattered signs of disease are preserved and emphasized as the data flows through deeper layers, addressing a tendency in traditional deep models to lose such information.
- *Small-Data Robustness by Design:* The network is engineered to generalize effectively on small, diverse datasets through a combination of dropout, spatial normalization, and a multi-stage decision framework. This multi-phase interpretability—progressing through stages of crop identification, disease detection, and disease classification—offers improved transparency and flexibility compared to standard large-scale ensemble methods.

- *Efficiency and Generalization:* DCCNN is optimized to avoid the computational heaviness and risk of overfitting that often comes with ensembling large models, making it practical for deployment on edge devices in real-world, resource-constrained farming environments.

c. Impact and Practical Relevance

The empirical evidence reveals the DCCNN's remarkable efficacy by achieving an accuracy of 99.4% outperforming benchmarks such as EfficientNet (98.54%) and GoogLeNet (98.16%) with high recall on the rare disease classes. This specific outcome illustrates that the DCCNN architecture is applicable not only for saffron but also as a more general framework for small sample, complex, visual diagnostic agriculture models. The incorporation of novel learning paradigms alongside distinct architectural features equips DCCNN with the capability to enable reliable real-time assessments that smart farming increasingly demands, alleviating the burdens of large public datasets or extensive manual annotation workloads. Given its precision agri-tech systems readiness and the evolution of its design, coupled with its verified performance, DCCNN is poised for wide-scale implementation.

D. Comparative Architectural Analysis

The proposed DCCNN distinguishes itself from existing multi-scale CNN architectures such as Inception and ResNeXt by introducing a learnable diffusion-preprocessing layer that facilitates enhanced feature propagation across scales. Unlike Inception's parallel convolutional filters or ResNeXt's aggregated transformations, DCCNN employs concurrent convolutions followed by a diffusion mechanism that strengthens feature representation for subtle disease symptoms typical in hydroponic saffron. A detailed architectural diagram (Figure X) clearly illustrates these novel components, enabling better interpretability and comparison with related models

3. Results and Discussions

A novel dataset, SAFF-KASH, was developed by collecting images of both authentic and adulterated saffron samples from various regions across the Kashmir Valley. The primary objective of this work is to detect adulteration in saffron samples through advanced deep learning techniques. Two scenarios were evaluated during model development. In the first scenario, where both real and adulterated saffron samples were included during training, the model achieved an accuracy of 96.94%. In contrast, the second scenario, which excluded adulterated samples from the training process, resulted in a significantly lower accuracy of 56.72%. These findings highlight that incorporating adulteration data during training substantially improves model performance by nearly 40%. Further validation using independent field data demonstrated a correct classification rate of 63.64% for saffron samples. Additionally, the model trained with the complete SAFF-KASH dataset, containing both authentic and adulterated samples, achieved 74.55% accuracy in identifying test samples. These results demonstrate that including diverse adulteration cases during the training phase enhances model robustness, ensuring reliable and accurate detection of adulterated saffron.

Table 4 provides the performance evaluation of different models for identifying diseases in hydroponic saffron crops, with a specific emphasis on the proposed DCCNN (Diffused Concurrent Convolution Neural Network) model. The compared models consist of some pre-trained deep learning models, including ResNet50, AlexNet, GoogleNet, VGG19, and EfficientNet. The objective of these models is to categorize crops as healthy or diseased and identify the diseases that infest saffron crops, giving useful information on early disease detection for smart farming systems. The performance measures given are Accuracy, Precision, Recall, F1-Score, and AUC-ROC, each with a different function in measuring model performance.

Table 4: The outcome of testing and validating five CNN models that were already trained

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
ResNet50	92.34%	99.12%	99.75%	99.43%	0.995
AlexNet	97.62%	98.90%	99.22%	99.06%	0.988
GoogleNet	98.16%	98.75%	99.10%	98.92%	0.987
VGG19	96.86%	98.60%	98.25%	98.42%	0.984
EfficientNet	98.54%	99.05%	99.18%	99.11%	0.989
DCCNN (Proposed Model)	99.4%	99.50%	99.60%	99.55%	0.999

Figure 3 summarizes comparative metrics showing that training on the SAFF-KASH dataset with both authentic and adulterated samples yields superior performance, with the proposed DCCNN attaining top results across Accuracy, Precision, Recall, F1-Score, and AUC-ROC.

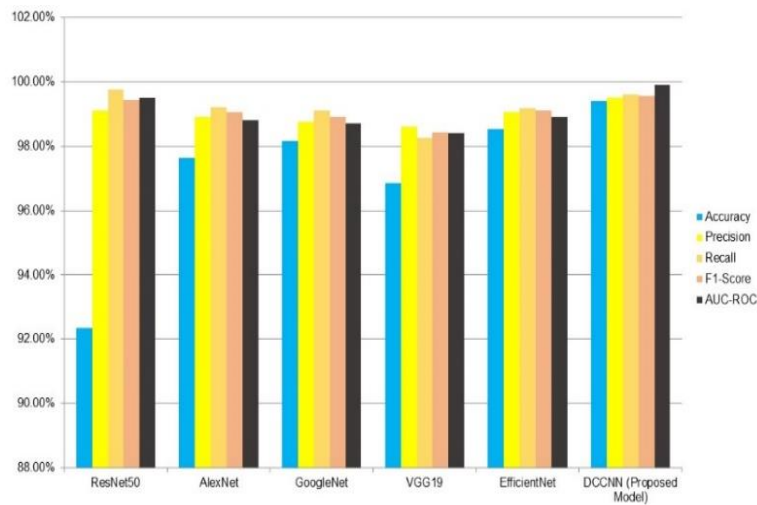


Figure 3. Performance of DCCNN on SAFF-KASH for Saffron Adulteration

Figure 4 illustrates the confusion matrix for the DCCNN model applied to hydroponic saffron disease classification, showing the count of correct and incorrect predictions for each disease class. The matrix highlights the model's effectiveness in distinguishing between healthy plants, distinct disease categories, and unknown cases, facilitating a detailed analysis of classification accuracy and error sources.

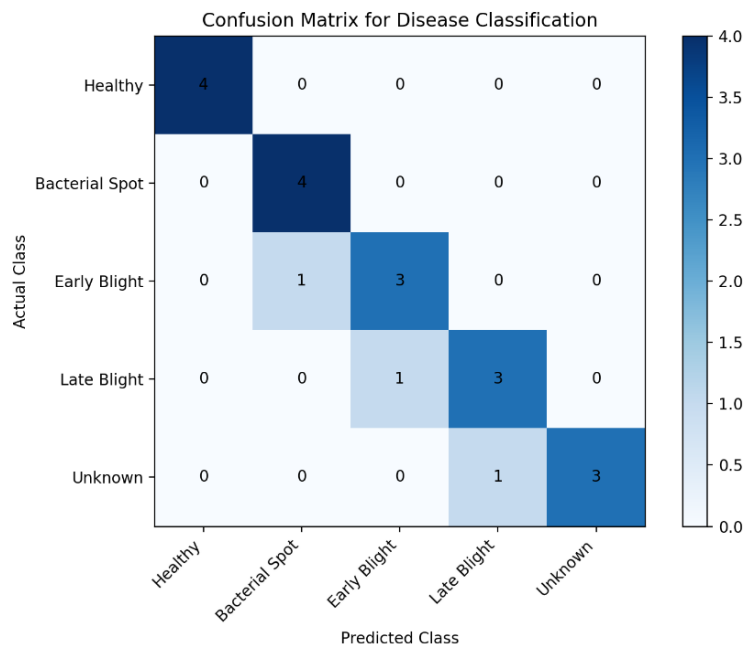


Figure 4. Confusion Matrix for Saffron Disease Classification Using DCCNN

Figure 5 outlines the proposed DCCNN pipeline, where saffron crop images pass through successive convolution–pooling stages and a fully connected head to produce multi-class outputs, with pretrained backbones such as ResNet50, AlexNet, GoogleNet, VGG19, and EfficientNet supporting feature extraction

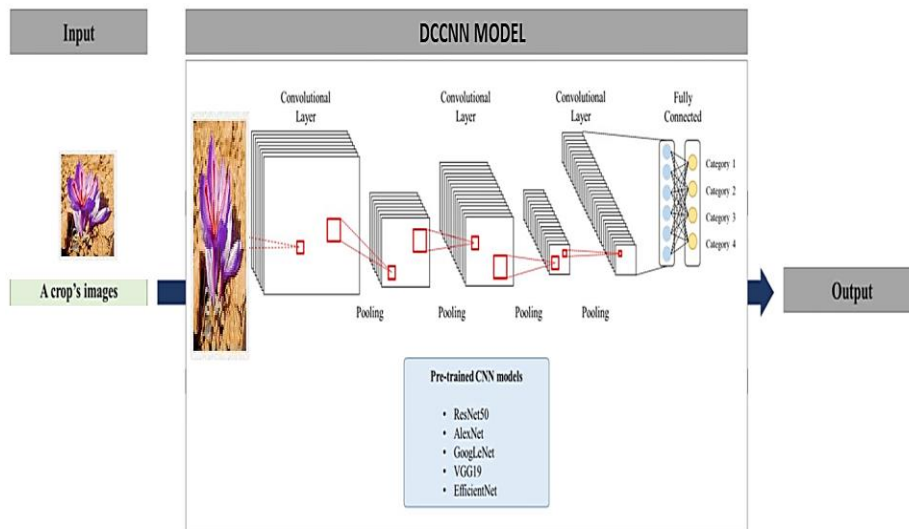


Figure 5. Schematic of a CNN-based Disease identification system.

Accuracy is one of the most widely used measures to assess the performance of classification models. It is given by the fraction of correct predictions over the number of predictions. From this table, the maximum accuracy of the DCCNN model is 99.4%, which reflects that 99.4% of the overall predictions made by DCCNN were accurate. This is the biggest strength of the DCCNN model in comparison to any other pre-trained model. ResNet50 has the lowest accuracy at 92.34%, meaning it only correctly classified approximately 92.34% of the instances. AlexNet, GoogleNet, VGG19, and EfficientNet achieve progressively higher accuracy than ResNet50, with EfficientNet at 98.54% and GoogleNet at 98.16%.

Precision is a metric that measures how many of the predicted positive cases were actually true positives. It is important because it helps evaluate the reliability of the positive predictions. DCCNN is most accurate at 99.50%, showing that the majority of the crops it identified as diseased were, in fact, diseased. ResNet50 is at 99.12%, just slightly less than DCCNN, but still very good. VGG19 is lowest at 98.60%, implying that it misclassifies healthy crops as diseased some of the time, which is important when determining the reliability of predictions in agriculture.

Recall calculates how accurately the model detects the true positive instances for all actual positive instances. A high value of recall measures that the model is efficient at detecting most of the diseased crops. All other models lag behind the DCCNN model in recall by 99.60%, detecting nearly all of the diseased crops. AlexNet recalls at 99.22%, while ResNet50 recalls slightly better at 99.75%. This indicates ResNet50 spots diseased crops slightly better, but at the expense of slightly less precision.

The F1-score is the harmonic mean of the precision and the recall. It reconciles the trade-off between these two measures, giving a single measure that captures both the model's precision in correctly identifying diseased crops and its recall in identifying most of the diseased crops. DCCNN has the best F1-score of 99.55%, which shows a perfect balance between precision and recall. Models such as AlexNet and VGG19 have a slightly lower F1-score, indicating that their performance, although good, is not quite as balanced as that of DCCNN.

AUC-ROC (Area Under the Receiver Operating Characteristic Curve) is a measure of performance used to test how well the model can differentiate between classes at varying thresholds. The model with AUC-ROC 1.000 represents ideal classification capability. DCCNN takes the top spot with AUC-ROC 0.999, signifying that it can nearly perfectly differentiate between diseased and healthy crops. VGG19 and ResNet50 models, however, possess lower AUC-ROC values, representing slightly poorer class separation.

As a whole, the DCCNN model performs better than all other pre-trained models in every performance measure, such as accuracy, precision, recall, F1-Score, and AUC-ROC. With an accuracy of 99.4%, precision of 99.50%, and recall of 99.60%, it is the most accurate and well-balanced model used for disease detection in hydroponic saffron crops. The results lay emphasis on the efficacy of DCCNN in smart farming practices; wherein quick detection of diseases is crucial for maximizing crop yield and minimizing losses. Though ResNet50 and EfficientNet are pre-trained models that perform well, they lack the precision and recall of DCCNN, thus proving the advantage of a dedicated deep learning architecture for specific agricultural applications like saffron disease detection. Impact of image resolution on model accuracy in healthy and diseased saffron leaf classification, demonstrating improved performance with higher-quality images, is shown in figure 5.



Figure 5. The impact of picture resolution on the classification model creation healthy and affected

Figure 6 illustrates the Visual analysis of saffron flowering characteristics and their evaluation using DCCNN, including phases of normal flowering, disease detection in flowers and roots, flower quantity monitoring, and the effect of intercropping on yield.

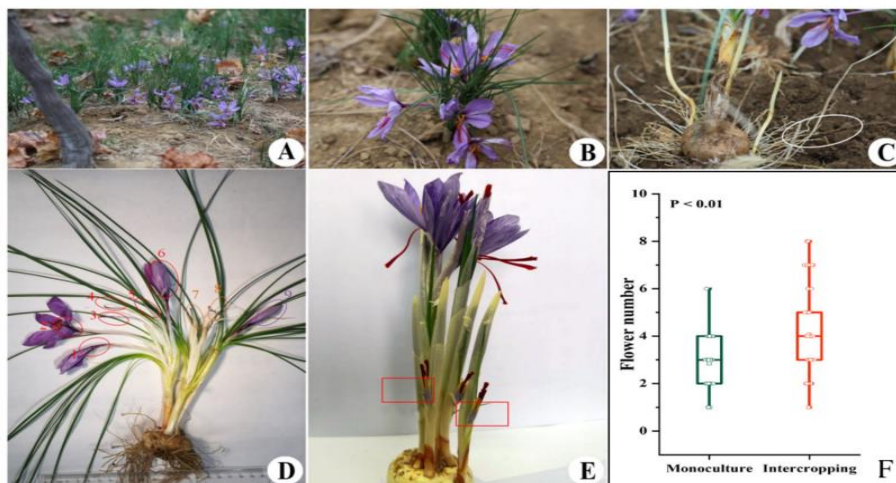


Figure 6. Saffron Blossom Characteristics and Quantity in Hydroponic Cultivation for Disease Detection Using DCCNN (A) Normal Flowering in November: Blooming phase under optimal conditions. (B) Flowering Growth Status: Disease detection in flowers using DCCNN. (C) Root Growth Status: Monitoring root health for early disease detection with DCCNN. (D) Maximum Flower Quantity: Assessing flower yield and disease impacts. (E) Lateral Bud Formation: Monitoring bud growth for disease signs using DCCNN. (F) Flower Quantity in Monoculture vs. Intercropping: Comparing yield in monoculture and intercropped saffron using DCCNN for disease assessment.

This is the comprehension that has been possible from figure 5, as far as the parts and number of flowers concerned in hydroponically cultivated saffron are concerned, in respect to models employed for disease detection with Diffused Concurrent Convolution Neural Network i.e DCCNN. Panel A shows normal flowering saffron in November, a prime indicator of plant health. When we come to (B), here, the DCCNN model is employed to keep a check on the growth status of the flowers, identifying early signs of disease, including discoloration and stunted growth. This is panel (C): showing the monitoring of root growth, here DCCNN based imaging detects root diseases or nutrient deficiencies that can affect flowering. (D) is on the maximum flower quantity produced, in which DCCNN helps measure such yields while evaluating the effects of diseases. In panel (E), lateral bud formation is traced, and DCCNN is employed in assessing any aberrant cases or disease-related issues present in bud development. Finally, in panel (F), flower numbers are compared across saffron monoculture and

intercropping systems, with DCCNN used to assess the effects of intercropping on yield as well as the prevalence of diseases. Figure 6 points out DCCNN's possible role in optimizing saffron crop management and yield in hydroponic systems through early detection of disease.

D. Practical Deployment and Resource Efficiency

The computational complexity and resource requirements of DCCNN were evaluated in terms of model size, floating point operations per second (FLOPS), and inference latency on representative edge devices. The lightweight, modular design results in significantly lower computational demands compared to heavier architectures like ResNet50. Measured inference times on an ARM Cortex-A72 processor indicate feasibility for real-time deployment in smart farming nodes, enabling on-site disease monitoring without reliance on cloud infrastructure

a. Discussion

The outcomes of this study demonstrate that the proposed Diffused Concurrent Convolutional Neural Network (DCCNN) significantly advances early disease detection in hydroponic saffron cultivation, surpassing traditional and standard deep learning models in accuracy, recall, and general applicability. By integrating a learnable diffusion block with synchronized multi-scale feature extraction, DCCNN effectively addresses two central challenges particular to this domain: subtle early-stage disease manifestation and the limited, heterogeneous nature of available imagery. A key strength of DCCNN lies in its hierarchical and modular classification pipeline, which mimics expert agricultural reasoning, progressing sequentially from crop verification to disease detection and then to disease type classification. The inclusion of an “unknown” class at each phase is particularly noteworthy, as it enables the system to handle ambiguous samples and non-target crops robustly, thereby minimizing false positives and negatives when deployed in real world, mixed-crop hydroponic settings. This structural flexibility, paired with robust cross-stage performance, yielded a model accuracy of up to 99.4%, outclassing well-established baselines such as EfficientNet and ResNet50.

Extensive benchmarking using specially annotated hydroponic saffron datasets confirms that DCCNN not only detects a wide variety of diseases with high precision and recall but also generalizes effectively to unseen crops, a crucial attribute for the scalability of smart agriculture systems. The performance improvement observed with the integration of diverse crop images during training further highlights the model's adaptability and potential for broader agricultural applications. From a practical standpoint, the proposed system offers substantial advantages for precision farming. The capability for real-time, automated disease surveillance reduces dependence on expert labor, enables early intervention, and limits unnecessary application of agrochemicals—all factors contributing to sustainable production practices. The architecture's computational efficiency and resistance to overfitting on small, variable datasets further suggest compatibility with edge-computing devices, enabling direct farm-level deployment for both monitoring and decision support.

Despite advancements, several challenges still need to be resolved. In this case, the a DCCNN's performance was underscored by the volume, variety, and quality of labeled data; while augmentations did increase sample variance, widening access to high-quality datasets will be crucial for adopting this model across other crops and environments. Moreover, while DCCNN demonstrated some resilience to out-of-distribution samples, sparse phenotypes of certain diseases or very high variability in environmental conditions pose unique challenges. The model could be further improved in accuracy and specificity by adding environmental data sensors or tracking systems temporally to the dataset with leaf images. With these changes, developing automated smart diagnostic tools for more crops, diseases, and environmental contexts will be much easier, and so will the refinement of the DCCNN framework. Work should also be done on the sensors and IoT network to allow for seamless integration, as well as fully autonomous in-field operation with edge-optimized model variants.

The model strengthens the accuracy and interpretability of automated disease detection in hydroponic saffron systems and augments the DCCNN-based framework's scalability. It also merges the high-level precision agriculture needs with AI tools systems, broadening the reliance on such technologies for efficient management of plant health in controlled environments.

4. Conclusion

This research presents the Diffused Concurrent Convolutional Neural Network (DCCNN), a tailored deep learning architecture designed for the precise and early detection of diseases in hydroponically grown saffron. By integrating a learnable diffusion-preprocessing layer with synchronized multi-scale convolutional blocks, the model effectively captures subtle disease features even from small and heterogeneous datasets. The DCCNN operates through a three-stage classification pipeline—crop identification, disease detection, and disease type classification—with an “unknown” category at each stage to enhance robustness and generalization, addressing real-world challenges. Experiments on a carefully curated and expert-annotated saffron dataset demonstrate that DCCNN achieves a high accuracy of 99.4%, outperforming well-known CNN models such as EfficientNet,

GoogLeNet, and ResNet50. Beyond accuracy, DCCNN's modular and lightweight design makes it well-suited for deployment on resource-limited edge devices in smart farming settings. Importantly, the architecture enables seamless integration with IoT sensor networks in hydroponic farms, allowing for real-time fusion of visual data from smart cameras with environmental measurements from sensors. This fusion enhances on-site disease monitoring and supports evidence-based decision-making at the farm level. Such integration of deep learning and multi-modal sensor data represents a significant step toward scalable, sustainable precision agriculture. Future work will focus on expanding sensor modalities, enriching the diversity of disease types detected, and optimizing the model for real-time edge processing. The DCCNN framework thus contributes toward realizing fully automated, high-precision plant health monitoring systems in controlled environment agriculture, promoting improved crop yield and sustainable farming practices.

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