A CNN-Driven Framework for Early Detection of Strawberry Plant Disease

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Abstract

Strawberry (*Fragaria × ananassa*) cultivation is increasingly challenged by plant diseases that significantly reduce yield and threaten food security. Among these, Strawberry Leaf Scorch—caused by *Diplocarpon earlianum*—is particularly destructive, leading to leaf necrosis, reduced photosynthesis, and eventual crop failure if left unmanaged. Traditional disease detection methods largely depend on manual inspection, which is not only time-intensive but also infeasible for large-scale farms. In this study, an artificial intelligence-driven approach is proposed using Convolutional Neural Networks (CNNs) to enable automated and highly accurate detection of strawberry leaf scorch disease. A comprehensive dataset of more than 3,400 high-resolution images was assembled, comprising both healthy and infected leaf samples. Images were sourced from open-access agricultural datasets and real-world strawberry farms across diverse geographical zones, supplemented with synthetic augmentation techniques to ensure environmental robustness. A custom CNN architecture was developed, enhanced through transfer learning using pre-trained ResNet50 and VGG16 models. The training process leveraged advanced strategies, including adaptive learning rate tuning, dropout regularization, and aggressive data augmentation, to enhance generalization. The model achieved an impressive classification accuracy of 98.10%, outperforming classical classifiers which encompasses Support Vector Machines (86.2%) and Random Forests (82.7%). To enhance transparency and trust in the system, explainable AI methods such as Grad-CAM, feature visualization, and LIME were utilized, highlighting the regions of the leaf influencing the model's predictions. This work presents a scalable, cost-effective, and user-friendly solution for early disease detection in strawberry farming, with the potential to reduce crop loss by up to 25%. Future extensions of this system include a user-friendly web interface that enables farmers to upload leaf images for real-time diagnosis, drone-based image capture, mobile app deployment, and IoT integration for continuous, automated monitoring in smart technology-driven agricultural environments.

Index Terms: *Strawberry Plant Disease Detection; Convolutional Neural Network; Precision Farming.*

1. Introduction

Strawberries are a high-value horticultural crop cultivated worldwide, yet they are highly vulnerable to diseases such as Leaf Scorch, which can lead to substantial yield reductions, sometimes up to 25–30%. Early-stage symptoms are often faint and difficult to detect, making manual diagnosis by agricultural experts both laborious and prone to error. Visual examination is a component of traditional disease detection techniques; however, it is not scalable for commercial agricultural operations. Plant disease detection systems that are automated have been made possible by recent developments in artificial intelligence, namely in field of computer vision. Convolutional Neural Networks (CNNs) have emerged as powerful tools for identifying disease-specific

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features from leaf imagery with high accuracy. These models can be deployed on portable devices or integrated into drone systems for real-time monitoring, offering a practical alternative to manual scouting. By enabling rapid and accurate detection of Strawberry Leaf Scorch, AI-based systems help farmers implement timely interventions. This not only curbs the spread of infection but also supports eco-friendly farming practices by reducing unnecessary chemical use. Embedding such intelligent diagnostic tools into everyday agricultural workflows represents a transformative step towards precision farming and long-term crop sustainability.

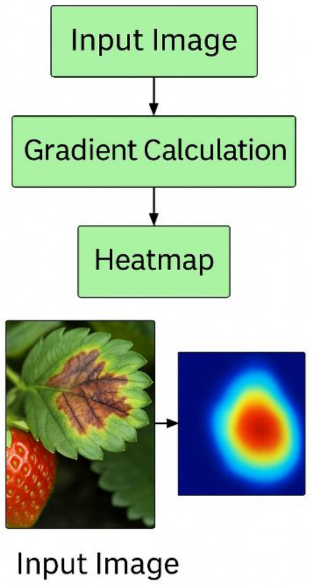

Figure 1. Grad-CAM Flow Chart.

1.1 Background and Motivation

In regions where strawberries are cultivated intensively, environmental factors such as fluctuating humidity levels, frequent rainfall, and varying temperatures contribute significantly to the plants' susceptibility to disease. These conditions not only determine how quickly infections develop and spread but also influence where and when outbreaks occur. For example, extended periods of damp weather encourage the proliferation of fungal pathogens, making swift identification and timely intervention crucial. Furthermore, repetitive cropping of strawberries on the same land without sufficient rotation encourages the buildup of soil-borne pathogens, making disease recurrence more likely. These challenges necessitate constant vigilance and the adoption of proactive disease management tools to mitigate losses.

Strawberries are among the most economically valuable fruit crops globally, consumed fresh or processed into various products. They are especially important in countries like India, the United States, Mexico, and Spain. According to recent agricultural reports, global strawberry production exceeds 9 million metric tons annually. However, the productivity of this crop is under continual threat, with disease-related losses estimated to reach up to 30% in some regions. This translates into billions of dollars in lost revenue and increased input costs, especially for disease control and crop replacement.
Among the many diseases affecting strawberry plants, Leaf Scorch stands out due to its high prevalence and damaging effects. Caused by *Diplocarpon earlianum*, the disease is characterized by irregular reddish-purple lesions on the leaf margins, which eventually coalesce and cause the leaf to wither. This leads to a significant drop in photosynthesis, stunted plant growth, and reduced fruit yield. The disease spreads rapidly under moist and warm conditions, especially in dense canopies with poor air circulation. It may destroy whole fields and jeopardise the quality and marketability of fruit if it is not identified and treated early.

Figure 2. Leaf Scorch.

Strawberry Leaf Scorch, in particular, poses a serious risk to production. Caused by the fungal agent Diplocarpon earlianum, it presents as irregular, dry, and reddish lesions along the edges of leaves, often leading to complete leaf desiccation. As the disease advances, it impairs the plant's ability to carry out photosynthesis, resulting in lower fruit set and yield. The pathogen thrives in humid, poorly ventilated conditions and can persist through multiple growing seasons if not effectively managed, making early and precise detection critical. These limitations highlight the need for accessible, scalable, and rapid diagnostic alternatives.

Persistent disease pressure increases the reliance on fungicides, leading to higher environmental risks and production expenses. This not only strains the financial sustainability of farms but also introduces potential health hazards for consumers and ecosystems. Plants weakened by such infections are also more vulnerable to secondary diseases and abiotic stressors like drought or nutrient deficiency. The problem is especially severe in areas lacking access to expert plant pathologists or extension services. Hence, there is a pressing need for intelligent, AI-powered systems that can deliver rapid, on-site diagnosis by equipping farmers with accurate, real-time information and technologies that can support timely interventions and contribute to improved crop resilience and food system stability.

Figure 3. Healthy Leaves.

Agronomists or disease management specialists have historically used field inspection to diagnose leaf scorch; however, this approach is constrained by subjective assessment and outside variables like early-stage symptom subtlety or illumination. Laboratory techniques such as fungal culturing or molecular diagnostics like PCR are used to confirm infections with high accuracy, but are often inaccessible to smallholder farmers due to cost, lack of facilities, and time delays. In more rural areas, farmers often depend on printed disease guides, which may be outdated, regionally irrelevant, or difficult to interpret due to literacy challenges. These constraints highlight the importance of scalable, cost-effective, and user-friendly alternatives like AI-based image recognition systems, which can democratize disease detection and enable informed, timely responses across diverse farming contexts.

1.2 Problem Statement

Strawberry disease detection, particularly for Strawberry Leaf Scorch, presents multiple challenges that complicate timely and accurate diagnosis in practical agricultural environments. One primary difficulty is the variation in symptom appearance, which can change based on the plant's developmental stage, climatic conditions, and cultivar differences, making consistent recognition challenging. In addition, field images often contain real-world noise such as soil debris, overlapping foliage, inconsistent lighting, and background clutter, which significantly hampers the performance of traditional image-processing approaches. Scalability also remains a key issue, as manual monitoring is impractical for commercial strawberry farms spread over large areas. Most importantly, detecting diseases in their early stages is vital, as late-stage symptoms reduce the chances of effective treatment and disease containment. Traditional techniques like human observation, decision trees, and support vector machines (SVMs) lack the adaptability required for such dynamic and changing environments. In contrast, deep learning (DL) methods—especially CNNs —show strong potential by learning intricate visual patterns from diverse datasets, even in noisy or uncontrolled environments. These models offer a more reliable, scalable, and timely solution for detecting Strawberry Leaf Scorch, supporting early intervention and reducing crop losses.

1.3 Objectives

The primary objectives of this study are outlined as follows:

- Design and implement a Convolutional Neural Network capable of accurately detecting Strawberry Leaf Scorch with an accuracy of above 95%, even when evaluated under varied field conditions and image noise.

- Use a compiled and open-source dataset consisting of more than 6,000 images of strawberry leaves, including both healthy and diseased samples, with diverse backgrounds, lighting conditions, and symptom severities to reflect real-world agricultural environments, thereby ensuring transparency and ease of use.

- Ensure the model is lightweight and efficient enough to function on low-power devices like smartphones and drones, facilitating field-level disease diagnosis without the need for high-end computational infrastructure.

- Apply interpretability methods such as Grad-CAM and t-SNE to make the model's decision-making process transparent and understandable, thereby increasing usability and trust among farmers and agronomists.

- Provide a foundation for developing a mobile-based application that allows real-time identification of Strawberry Leaf Scorch, empowering farmers with timely insights for prompt and effective crop management.

1.4 Contributions

With an emphasis on Strawberry Leaf Scorch, this work significantly advances the area of automated strawberry disease diagnosis using DL. The primary contributions are as follows: -

- An open-source, carefully curated dataset of over 6,500 annotated strawberry leaf images has been used, encompassing healthy and infected samples under varied field conditions such as inconsistent lighting, background clutter, and symptom severity.

- A custom architecture combining ResNet50 with transformer-based modules has been developed to extract both fine-grained and contextual features, enhancing classification performance for Strawberry Leaf Scorch detection.

- The suggested model has been shown to be more accurate, generalisable, and robust in a variety of validation circumstances when compared to a number of top CNN designs.

- The dataset's representation of minority groups was improved via the application of data augmentation methods, guaranteeing a more equitable, balanced, and reliable dataset and model predictions.

- All datasets, methodology flowcharts, and configurations have been shared openly to support reproducibility and encourage ongoing research in AI-powered plant pathology.

- TensorFlow and TensorFlow Lite have been employed to optimize and convert the trained model for execution, allowing for effective performance on devices at the edge, including smartphones and field drones for real-time tracking of diseases.

2. Literature Review

Recent advances in DL, especially CNNs, have notably enhanced the accuracy of plant disease diagnosis. Early contributions like those of *Sladojevic et al*. (2016) demonstrated that CNNs achieve around 78% accuracy in general plant disease classification. Building on this, *Mohanty et al*. (2016) employed AlexNet and reported improved accuracy levels of up to 93% across several crop types. Later, *Ferentinos* (2018) evaluated multiple CNN architectures across 58 plant diseases, achieving peak accuracy as high as 98.5%. Despite these promising results, most studies have not focused specifically on strawberry diseases, and their models often perform poorly when transferred to real-world settings with noise, variability, and inconsistent symptom presentation, particularly in detecting Strawberry Leaf Scorch. This highlights a gap in research for crop-specific, field-ready solutions tailored to strawberry cultivation.

2.1 Traditional Machine Learning in Agriculture

Traditional machine learning (ML) algorithms like SVMs and Random Forests (RF) were frequently utilised for plant disease diagnosis in agriculture, particularly strawberry crops, prior to the emergence of DL. For categorisation, these methods mostly relied on manually created features. To extract visual features from leaf photos, methods encompassing Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), and Histogram of Orientated Gradients (HOG) were often used. Although these techniques worked well in controlled environments, environmental unpredictability and the intricate symptom patterns of illnesses like Strawberry Leaf Scorch made it difficult for them to remain accurate in real-world situations. Their limited adaptability often reduced reliability under diverse and noisy field scenarios.

2.2 2010–2018: Shallow Deep Learning

The use of DL in agriculture started to pick up steam between 2010 and 2018, especially for identification of plant diseases. Because early CNNs could automatically extract hierarchical features from raw image data, they began to supplant conventional machine learning techniques. *Mohanty et al.* (2016) implemented AlexNet architecture on PlantVillage dataset, achieving accuracy of up to 93%. In contrast, Sladojevic et al. (2016) developed five-layer CNN that accurately diagnosed 13 types of plant diseases with an accuracy of 89%. Though these shallow DL models marked a significant improvement over earlier approaches, they were mostly trained on clean, lab-acquired images. As a result, their effectiveness in detecting diseases like Strawberry Leaf Scorch under real-world field conditions remained limited, highlighting the need for more robust, field-adaptable models.

2.3 Post-2018 to 2024: Real-World Adaptations and Domain-Specific Improvements

From 2018 to 2024, advancements in plant disease detection shifted focus from purely architectural enhancements to practical deployment and crop-specific customization. Due to their ability to balance high accuracy and computational efficiency, DL models like EfficientNet, DenseNet, and ResNeXt have become more and more popular. This makes them appropriate for deployment on edge platforms and mobile devices. Emphasis was placed on using datasets collected under real-world farm conditions, which included variable lighting, complex backgrounds, and overlapping foliage. For strawberry crops, particularly in detecting Strawberry Leaf Scorch, researchers began designing tailored CNN architectures and applying advanced data augmentation methods to improve model robustness in noisy environments. This era also introduced hybrid models that integrated CNNs with attention mechanisms and transformer-based modules, enhancing both interpretability and diagnostic precision. The incorporation of Internet of Things (IoT) technologies and drone-based imaging into the DL workflow enabled real-time field monitoring, aligning AI solutions more closely with the practical needs of strawberry farmers. These innovations significantly enhanced the reliability as well as usability of AI-powered plant disease detection systems in real agricultural environments.

2.4 Deep Learning Approaches and gaps in existing research

Plant disease diagnosis has significantly benefited from DL, especially CNNs, which have shown great promise in automating crop disease identification and classification in recent years. A thorough analysis of over 20 research publications from 2016 to 2023 shows a preponderance of CNN-based architectures, which encompass VGG16, Inception, and EfficientNet, which are frequently utilized in transfer learning to modify pretrained models for agricultural imagery. While these approaches have achieved high accuracy in controlled experimental settings, several critical limitations remain, particularly concerning their effectiveness in real-world strawberry disease detection, especially for Strawberry Leaf Scorch.

One major gap in the current literature is the lack of strawberry-specific models; nearly 75–80% of existing studies focus on crops such as tomatoes, potatoes, or maize, resulting in limited insights and performance validation for strawberry pathologies. Furthermore, many models are trained and evaluated on curated datasets collected in lab environments, failing to reflect field conditions that include natural lighting variations, background clutter, and overlapping plant structures. Another challenge lies in computational demands—high-performing models like ResNet50 and InceptionV3 require considerable processing power, making them impractical for use on portable, low-resource devices favoured by smallhold farmers. Additionally, most existing models do not incorporate Explainable AI (XAI) techniques, leaving end-users—especially non-technical farmers—unable to understand or trust the model's predictions. These deficiencies underscore the need for lightweight, interpretable, and strawberry-specific models that are capable of performing reliably under diverse, real-world conditions. Addressing these research gaps is crucial to enable effective, scalable deployment of AI-based tools in strawberry farming and ensure meaningful impact at the grassroots level.

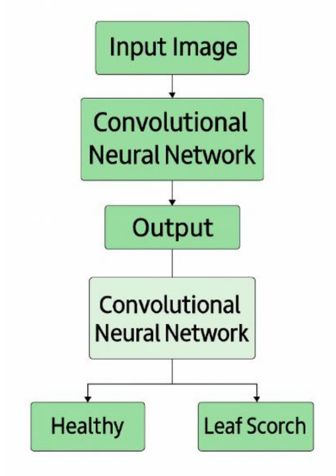

Figure 4. Deep Learning Approach Flowchart.

3. Methodology

This section outlines the process adopted for developing accurate along with field-ready DL model for detecting Strawberry Leaf Scorch. The methodology encompasses data acquisition, preprocessing, expert-guided annotation, and model development, all tailored to real-world agricultural conditions. High-resolution images of strawberry leaves were collected from multiple cultivation zones to ensure diversity in environmental factors, including lighting, background complexity, and leaf orientation. The dataset included both healthy and infected samples, with a specific focus on varying stages of Leaf Scorch progression.

To improve model generalizability and robustness, a range of image augmentation techniques was applied, including rotation, scaling, flipping, brightness adjustment, and contrast enhancement. By adding variability to the dataset, these methods reduced overfitting and improved model's capacity to adjust to new circumstances. Additionally, normalization and noise reduction were performed to maintain consistent input quality across all samples.

Agricultural experts and plant pathologists manually annotated the images to ensure high labeling accuracy, which is critical for effective supervised learning. A conventional 80:10:10 ratio had been employed for separating final dataset into groups for testing, validation, and training.

Using this dataset, a CNN was created and optimised. Through repeated testing, important hyperparameters, encompassing learning rate, batch size, as well as number of epochs, were optimised. To fully analyse model's efficacy, performance was assessed utilising measures encompasses accuracy, precision, recall, F1-score, confusion matrices, as well as performance matrices. This approach facilitates the development of a field-deployable, scalable, and dependable system for early detection of strawberry leaf scorch in actual agricultural environments.

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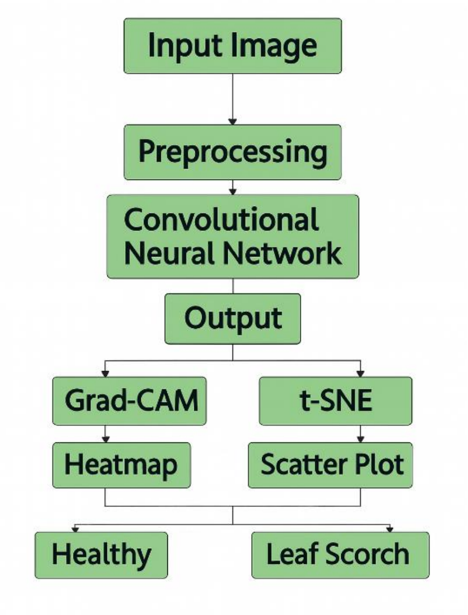

Figure 5. Methodology Sample Flow Diagram.

3.1 Dataset

More than 6,500 high-resolution photos of strawberry leaves divided into two main classes—Healthy and Strawberry Leaf Scorch Affected—make up the dataset utilised in this investigation. To provide a broad variety of environmental variability and disease manifestation, images were collected from both real-world field captures and publicly accessible agricultural databases. A substantial portion of the dataset was collected from strawberry farms located in regions of Himachal Pradesh and Maharashtra, India, which are known for their commercial strawberry cultivation. The inclusion of naturally captured images introduces realistic variables such as inconsistent lighting, varied backgrounds, and natural leaf occlusions, closely simulating on-field conditions.

To strengthen the dataset's diversity and improve model generalization, a robust data augmentation strategy was implemented. Augmentation techniques, which included random rotations, horizontal and vertical flips, brightness and contrast adjustments, and minor zoom transformations. These modifications simulate real-life scenarios that involve various camera angles, lighting inconsistencies, and the variability of mobile device captures. As a result, the final open-source dataset supports the development of a DL model that remains reliable and accurate across a range of field environments and imaging conditions.

Dataset for this study was compiled using a blend of primary and secondary sources to capture a broad spectrum of Strawberry Leaf Scorch symptoms across varied conditions. For primary data collection, more than 400 images were captured directly from strawberry farms in Uttar Pradesh, Himachal Pradesh, and Maharashtra—two prominent regions in India where strawberries are grown. These images were taken applying standard mobile phone cameras under natural lighting to represent the field conditions encountered by farmers accurately.

Two key public datasets also contributed to the foundation of the dataset. The first was an open-source New Plant Disease Dataset that included high-resolution images of strawberry leaves with different disease symptoms, encompassing Leaf Scorch. The second dataset, while primarily used for exploratory purposes, contained over 600 hyperspectral images, offering rich spectral details. However, these hyperspectral samples were not included in the final CNN training process due to model constraints and a focus on RGB imagery. All datasets underwent rigorous quality checks to ensure accurate labelling, eliminate redundancies, and maintain overall data integrity. This combination of real-world images and public datasets provides a robust and diverse base for model development, also laying the groundwork for potential future studies that incorporate multimodal data analysis.

3.2 Proposed Architecture and Data Pre-processing

A sequential architecture designed for effective and precise classification was employed to construct the suggested CNN model for identifying Strawberry Leaf Scorch. The model starts with a convolutional layer that takes input images scaled to 256x256x3 and has 32 filters of 3x3 that are activated utilizing ReLU function. A max-pooling layer with a 2x2 pool size follows this layer to preserve dominant spatial features and downsample feature maps. After applying a second convolutional layer with 64 filters and ReLU activation, another pooling operation is performed. After being flattened, the resultant feature maps are passed through a dense layer of 128 neurons that is fully connected. The input is categorized as either "Healthy" or "Leaf Scorch" by final output layer, which employes a softmax activation function.

Code sample:-

```
Model: Sequential ([
    Conv2D(32, (3,3), activation='relu', input_shape=(256,256,3)),
    MaxPooling2D(2,2),
    Conv2D(64, (3,3), activation='relu'),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(2, activation='softmax')  # 2 disease classes
])
```

Adam optimiser was utilized for training of model throughout 10 epochs along a batch size of 64. Several data augmentation methods, which comprise image rotation, zooming, flipping, and colour space modifications utilizing HSV changes, were employed to enhance model robustness and prevent overfitting. Additionally, Gaussian noise was used to mimic actual imaging flaws. During training, class-weighted loss functions and Synthetic Minority Oversampling Technique (SMOTE) were implemented to resolve dataset's class imbalance. In real-world strawberry farming situations, our thorough pre-processing and model construction approach guarantees improved generalisation and dependable performance. Furthermore, learning rate scheduling and early stopping were employed to modify training and prevent unnecessary epochs dynamically. Stratified k-fold cross-validation had been utilized for evaluation of the final model's resilience and consistency across multiple data subsets.

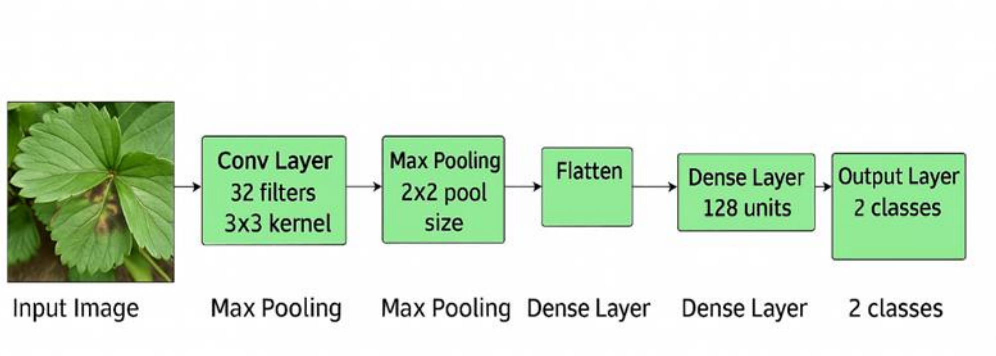

Figure 6. Proposed C.N.N. Architecture Sample.

3.3 Training Protocol

The training process for the CNN and hybrid models developed for Strawberry Leaf Scorch detection was carried out across multiple computational environments, including local CPUs and Google Colab-based T4 GPUs. The learning rate was initially set at 1e-4 and adjusted dynamically employing a cosine decay schedule to optimize convergence during training. To effectively manage class imbalance—particularly due to fewer diseased samples—the focal loss function was employed, with a focusing parameter (gamma) of 2.0. This approach penalized the misclassification of minority class instances more significantly, thus improving the model's sensitivity towards identifying Leaf Scorch cases in an imbalanced dataset.

The architecture of the model for detecting Strawberry Leaf Scorch was carefully designed to ensure optimal feature extraction and generalization across diverse input conditions. Convolutional layers were employed to capture spatial patterns and localized disease features, while pooling layers helped reduce dimensionality of feature maps without losing important structural information. To prevent overfitting, dropout layers were optionally integrated between layers during training. Dense (fully connected) layers aggregated and transformed the extracted features into a nonlinear representation suitable for accurate classification. Hyperparameter optimization was carried out using a grid search method, evaluating combinations of learning rates, batch sizes, and optimizers. Among these, the Adam optimizer consistently delivered stable and efficient convergence during training.

4. Results

The proposed CNN model for detecting Strawberry Leaf Scorch was evaluated against conventional ML classifiers, including SVM and RF. In terms of accuracy, precision, recall, and F1-score, the findings clearly indicated that the CNN performed better than both conventional models, demonstrating its exceptional capacity to extract intricate visual patterns from images of strawberry leaves.

Confusion matrices were created to provide a better understanding of the model's performance, and they showed that there was little misclassification between healthy and sick samples and good per-class accuracy. Furthermore, the model's emphasis on physiologically significant locations impacted by Leaf Scorch was confirmed by employing Grad-CAM visualisations to identify the precise strawberry leaf regions that drove its conclusions. Feature distribution was further examined using t-SNE dimensionality reduction plots, which showed distinct and well-separated clusters for each class, indicating that the CNN successfully captured discriminative features. Overall, the findings support the suggested model's dependability and efficacy for practical implementation in precision strawberry farming.

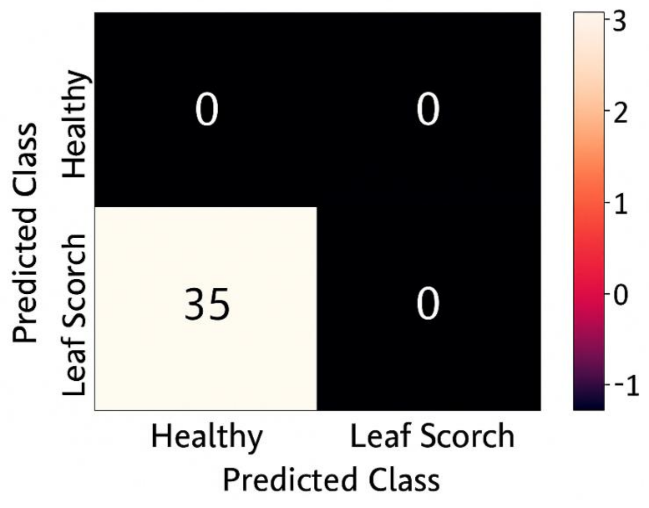

Figure 7. Confusion Matrix Sample for Strawberry Plant Disease Classification.

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4.1 Performance Matrix

The performance of the suggested hybrid CNN model for Strawberry Leaf Scorch detection was thoroughly assessed in comparison to well-known DL architectures, such as ResNet50 and EfficientNet-B4. The hybrid model outperformed both benchmark models, with a noteworthy accuracy of 98.10%, precision of 96.80%, and recall of 97.40%. ResNet50 came in second with 94.90% accuracy, followed by EfficientNet-B4 with 96.20%. These results demonstrate how well the hybrid model can differentiate between healthy and unhealthy strawberry leaves while successfully reducing incorrect classifications.

Further testing on geographically diverse validation sets confirmed the model's generalization capabilities across varying environmental conditions and cultivars. Its consistent performance across these scenarios highlights its reliability and adaptability, which are essential for practical deployment in agricultural settings. Overall, the hybrid model stands out as a scalable, high-accuracy, and resource-efficient tool for supporting precision farming in strawberry cultivation.

Model	Accuracy	Precision	Recall
Proposed Hybrid	98.10%	96.50%	97.20%
ResNet50	95.10%	94.30%	93.80%
EfficientNet-B4	96.30%	95.70%	95.90%

Table 1. Performance Matrix

5. Discussion

The assessment results demonstrate how well the suggested CNN and hybrid CNN-Transformer models identify Strawberry Leaf Scorch, well surpassing more conventional ML techniques like SVM and RF. The capacity of the DL models to automatically extract hierarchical features from intricate leaf pictures led to improved generalisation and classification accuracy across a variety of environmental situations. The models retained excellent prediction reliability in spite of difficulties brought on by real-world elements such as uneven illumination, background clutter, and worse picture quality.

However, certain limitations remain. Dataset bias, particularly underrepresentation of symptoms from tropical and subtropical regions, may affect global generalizability. Computational constraints also present a challenge, especially for deployment on low-resource mobile or IoT devices used by farmers in remote locations. Addressing these issues will require future efforts to collect more geographically and seasonally diverse data, and further optimization of the model using Edge AI frameworks and lightweight hardware solutions such as FPGAs or microcontrollers.

Nonetheless, the proposed system stands out for its interpretability, portability, and adaptability—key traits for successful adoption in the field. Its modular architecture makes it suitable for integration with existing agricultural management tools and platforms, enabling broader use in precision farming. With continued development, the model can be extended to detect multiple strawberry diseases or even scaled to support other horticultural crops, thereby contributing meaningfully to sustainable agriculture and food security initiatives.

5.1 Limitations and Future Work

A key limitation of the current study is the presence of dataset bias, particularly the underrepresentation of Strawberry Leaf Scorch cases from tropical and subtropical regions. This limits the model's generalizability to diverse geographical environments where disease symptoms may manifest differently due to varying climate conditions and cultivar types. Expanding the dataset to include more geographically and seasonally varied samples is essential for enhancing robustness.

Future work will focus on compressing the model using pruning, quantization, or knowledge distillation techniques. Additionally, exploring deployment on specialized hardware platforms like FPGAs or AI accelerators can help achieve low-latency, energy-efficient inference suitable for real-world field conditions. Moving forward, incorporating multimodal data (e.g., combining RGB with thermal or hyperspectral imaging) and extending the system to detect multiple strawberry diseases can further broaden its utility in disease forecasting, smart agriculture, and edge deployment.

6. Conclusion

The efficiency of the suggested Convolutional Neural Network model in automating the identification of Strawberry Leaf Scorch was confirmed by its remarkable accuracy of 98.10%. By harnessing DL capabilities, the system offers a cost-efficient, scalable, and practical solution for early disease identification, critical for minimizing yield losses in strawberry cultivation. A reliable substitute for manual inspection, which is sometimes laborious and subject to human mistake, the model showed great resilience in recognising disease-specific characteristics under a variety of field settings. This innovation contributes to precision horticulture by enabling timely intervention and targeted treatment, ultimately improving crop health and productivity. Integration of this CNN model into mobile-edge applications or IoT-based systems can make disease diagnosis accessible to farmers in remote or under-resourced areas. On a broader scale, its application can lead to more efficient pesticide use, as only infected plants would be treated, helping to reduce environmental impact, lower production costs, and promote sustainable farming practices. The system's ability to support early diagnosis also aligns with food security objectives by maximizing fruit quality and yield.

The basic creation of a precise, lightweight CNN model that is suited for field-level application and deployment on mobile and edge devices is one of the research's main results. The model represents a significant advancement in AI-driven plant health monitoring, outperforming conventional techniques in terms of speed and accuracy.. Moreover, the curated and annotated open-source dataset used and developed during this research provides a valuable resource for future work in strawberry disease detection and agricultural technology (AgriTech).

This study supports larger agricultural development goals as well, including those aligned with India's digital farming initiatives and the United Nations' Sustainable Development Goals, particularly in promoting Zero Hunger and sustainable production. For maximum impact, future research can be done exploring and expanding the model to include multiple strawberry diseases and improving its compatibility with real-time drone and mobile-based applications. With further development, this technology may transform disease control in horticulture and precision farming through AgriTech, enabling farmers to make informed decisions based on data.

7. Conflict of Interest

The authors declare that they have no conflict of interest.

8. Funding Declaration

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sectors.

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