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A Comparative Hybrid CNN-SVM Framework for Multi-Crop Nutrient Deficiency Classification Using Leaf Pattern Analysis

Suresh Kumar Thakur1, Anupa Sinha2, Meeta Dewangan3

1Ph.D. Scholar, Department of CS, Kalinga University, Naya Raipur, Chhattisgarh, India
2Assistant Professor, Department of CS & Faculty of IT, Kalinga University, Chhattisgarh, India
3Asst Professor, Department of Computer Science, Indira Gandhi Govt. P.G. College, Vaishali Nagar, Bhilai, Chhattisgarh, India
1suresh.thakur@kalingauniversity.ac.in, 2anupa.sinha@kalingauniversity.ac.in, 3meeta_dewagan1@outlook.com
Corresponding author: suresh.thakur@kalingauniversity.ac.in

Abstract

Early and accurate identification of nutrient deficiency in vegetable crops is essential for improving crop productivity, reducing yield loss, and supporting precision agriculture. Visual symptoms of nutrient deficiency commonly appear on leaves in the form of chlorosis, necrosis, marginal yellowing, interveinal discoloration, and structural deformation. However, manual identification is difficult because deficiency symptoms vary across crop species and may overlap among single and combined nutrient stress conditions. This study presents a comparative hybrid deep learning-Support Vector Machine framework for multi-crop nutrient deficiency classification using leaf image pattern analysis. A 36-class dataset was used, consisting of eight vegetable crops: ash gourd, bitter gourd, bottle gourd, cucumber, eggplant, ridge gourd, snake gourd, and tomato. The dataset included healthy and nutrient-deficient categories representing nitrogen deficiency, potassium deficiency, nitrogen-potassium deficiency, nitrogen-magnesium deficiency, and potassium-magnesium deficiency, depending on crop-specific class availability.

In the proposed framework, deep convolutional neural networks were used as feature extractors, and Support Vector Machine was used as the final classifier. Six CNN-SVM combinations were evaluated: MobileNetV2 + SVM, DenseNet121 + SVM, ResNet50 + SVM, EfficientNetB0 + SVM, VGG16 + SVM, and CustomCNN_Untrained + SVM. The dataset contained 12,600 training images, 2,700 validation images, and 2,700 testing images across 36 classes. Experimental results demonstrated that EfficientNetB0 + SVM achieved the highest test accuracy of 87.78%, with macro precision of 0.8787, macro recall of 0.8778, and macro F1-score of 0.8774. DenseNet121 + SVM achieved the second-best accuracy of 86.07%. The results confirm that hybrid CNN-SVM models can effectively classify multi-crop nutrient deficiency patterns using deep leaf image features. The proposed approach provides a rapid, non-destructive, and cost-effective decision-support method for crop nutrient stress diagnosis and may be extended to mobile and web-based precision agriculture applications.

Keywords: Nutrient deficiency; Deep learning; CNN; SVM; EfficientNetB0; DenseNet121; leaf pattern analysis; vegetable crops; precision agriculture.

1. Introduction

Vegetable crops play an important role in food security, nutrition, and agricultural income. Their productivity depends on proper nutrient availability, irrigation, climatic suitability, and timely crop management. Among different crop production constraints, nutrient deficiency is one of the major factors affecting plant growth, photosynthesis, flowering, fruit development, and yield quality. Deficiencies of nitrogen, potassium, and

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magnesium are especially important because these nutrients are directly associated with chlorophyll formation, enzyme activation, osmotic regulation, photosynthesis, and physiological metabolism [1], [2].

Nutrient deficiency symptoms are commonly expressed through visible changes in leaves. Nitrogen deficiency generally appears as reduced greenness, yellowing of older leaves, weak vegetative growth, and poor plant vigour. Potassium deficiency is often associated with marginal chlorosis, leaf scorching, necrosis, and reduced stress tolerance. Magnesium deficiency commonly produces interveinal chlorosis because magnesium is a central element of chlorophyll. In real crop conditions, these symptoms may overlap with each other, especially when combined deficiencies such as nitrogen-potassium, nitrogen-magnesium, or potassium-magnesium occur together. This symptom similarity makes manual diagnosis difficult and increases the possibility of incorrect nutrient management decisions [3], [4].

Traditional diagnosis of nutrient deficiency depends on farmer experience, expert visual inspection, soil testing, and laboratory-based leaf analysis. Although laboratory methods are reliable, they are time-consuming, costly, and not easily accessible to many small and marginal farmers. Manual visual inspection is faster but subjective, and its accuracy depends on the experience of the observer. Therefore, automated image-based diagnosis has become an important research direction in precision agriculture because it provides a rapid, non-destructive, and cost-effective alternative for plant health monitoring [5], [6].

Deep learning, especially Convolutional Neural Networks (CNNs), has shown strong potential in plant image classification because CNNs can automatically learn discriminative features from raw images. These features include colour variation, texture, chlorosis, necrosis, marginal symptoms, and leaf structural patterns [7], [8]. Earlier studies have successfully applied CNN-based approaches for plant disease identification, crop classification, and leaf pattern analysis [9]-[12]. However, nutrient deficiency classification is more challenging than ordinary disease classification because deficiency symptoms are often gradual, subtle, and visually similar across crop species and deficiency categories [13], [14].

To improve classification performance, hybrid deep learning and machine learning approaches have been explored. In hybrid CNN-SVM models, CNN architectures are used as feature extractors, while Support Vector Machine is used as the final classifier. SVM is effective in high-dimensional feature spaces and can produce strong decision boundaries between visually similar classes [19], [20]. This combination is useful for agricultural image datasets where symptoms may overlap and labelled samples may be limited compared with large general image datasets. In this study, a comparative hybrid CNN-SVM framework is proposed for 36-class multi-crop nutrient deficiency classification using leaf pattern analysis.

2. Related Work

Early plant image analysis studies mainly relied on image processing techniques such as colour thresholding, segmentation, edge detection, texture extraction, and handcrafted feature engineering. These features were commonly classified using machine learning algorithms such as Support Vector Machine, k-Nearest Neighbour, Decision Tree, Random Forest, and Artificial Neural Networks. Although these methods produced useful results, their performance depended heavily on manually selected features and controlled imaging conditions [15], [16].

The introduction of deep learning significantly improved image-based plant diagnosis. Mohanty et al. demonstrated that deep CNNs can classify plant diseases using leaf images with high accuracy, showing the feasibility of deep learning for plant health monitoring [1]. Ferentinos developed deep learning models for plant disease detection and diagnosis and reported strong performance across different CNN architectures [2]. Kamilaris and Prenafeta-Boldu reviewed deep learning applications in agriculture and highlighted their use in image-based crop monitoring, plant disease diagnosis, and agricultural decision support [3]. Barbedo discussed important

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factors that influence plant disease recognition, including image background, symptom similarity, dataset quality, and acquisition conditions [4].

Several studies have applied transfer learning models for plant disease and leaf classification. Too et al. compared fine-tuned deep learning models for plant disease identification and showed that pre-trained CNNs can provide strong classification performance [5]. Sladojevic et al. used deep neural networks for plant disease recognition using leaf image classification [7]. Geetharamani and Pandian proposed a deep CNN model for plant leaf disease identification [8]. Agarwal et al. developed an efficient CNN model for tomato crop disease identification [9], while Rangarajan et al. used pre-trained deep learning models for tomato crop disease classification [10].

CNN architectures such as ResNet, DenseNet, MobileNetV2, EfficientNet, and VGG16 have been widely used as feature extractors in image classification tasks. ResNet introduced residual learning to train deeper networks effectively [21]. DenseNet introduced dense connections to improve feature reuse and gradient flow [22]. MobileNetV2 introduced inverted residuals and linear bottlenecks, making it suitable for lightweight applications [23]. EfficientNet introduced compound scaling to balance depth, width, and resolution, improving accuracy and computational efficiency [24]. VGG16 remains a commonly used baseline architecture due to its simple stacked convolutional design [25].

Nutrient deficiency classification has recently gained attention because of its importance in precision agriculture. Bera et al. proposed PND-Net for plant nutrition deficiency and disease classification using graph convolutional learning, highlighting the need to capture regional leaf features for more accurate diagnosis [29]. However, multi-crop nutrient deficiency classification remains challenging because symptoms may vary across crop species and may overlap among single and combined nutrient deficiencies. Therefore, comparative evaluation of hybrid CNN-SVM models is useful for identifying robust feature extractors for nutrient stress classification.

3. Materials and Methods

3.1 Dataset Description

The experiment used a 36-class multi-crop nutrient deficiency image dataset. The dataset included leaf images from ash gourd, bitter gourd, bottle gourd, cucumber, eggplant, ridge gourd, snake gourd, and tomato. The classes represented healthy conditions and nutrient-deficient conditions, including potassium deficiency, nitrogen deficiency, nitrogen-potassium deficiency, nitrogen-magnesium deficiency, and potassium-magnesium deficiency depending on crop-specific availability. The dataset was divided into training, validation, and testing sets. The training set contained 12,600 images, the validation set contained 2,700 images, and the testing set contained 2,700 images. All three dataset splits contained 36 classes, and no class was missing from validation or testing.

Table 1. Dataset split used in the experiment

Dataset split	Number of images	Number of classes
Training set	12,600	36
Validation set	2,700	36
Testing set	2,700	36
Total	18,000	36

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3.2 Proposed Experimental Workflow

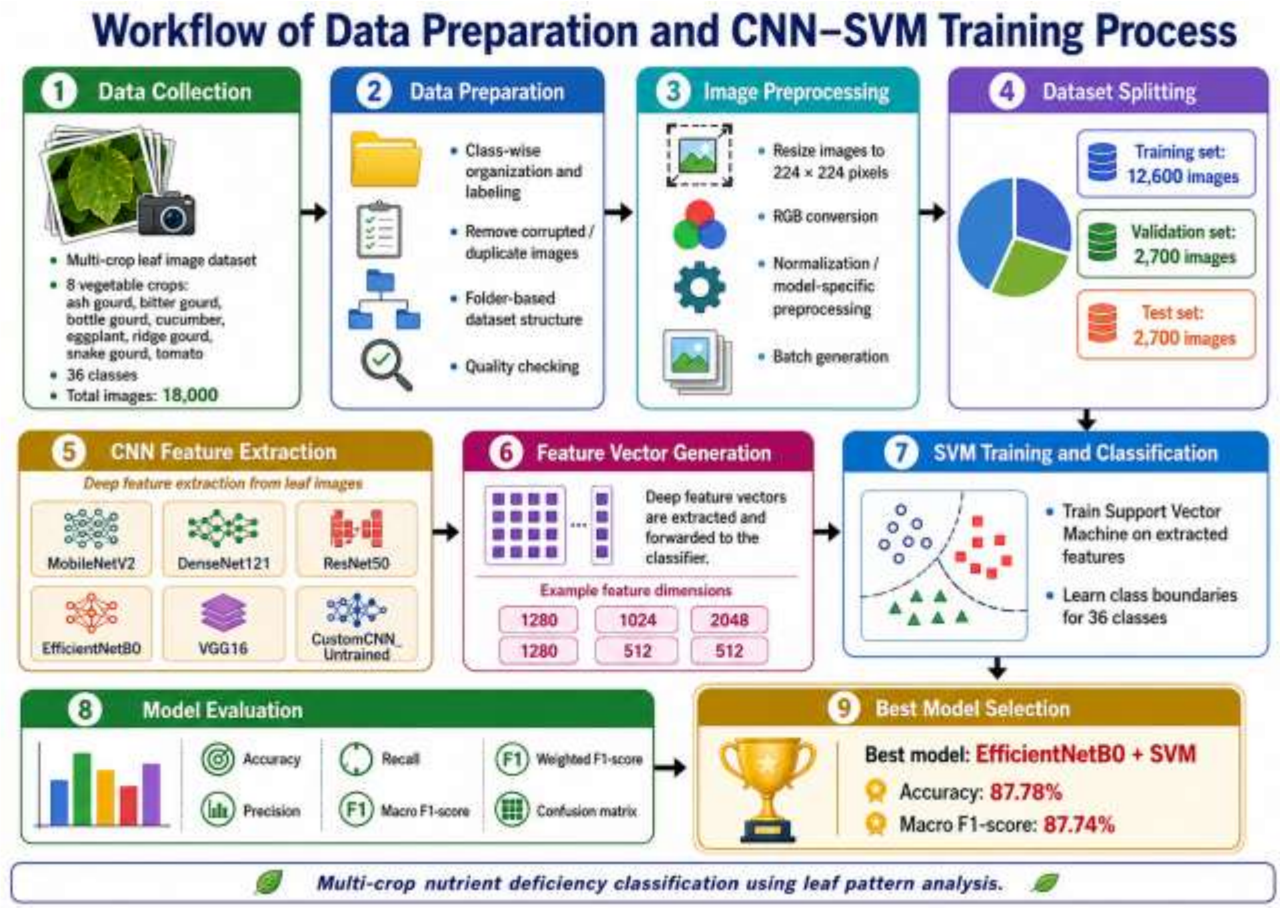

Figure 1. Workflow of data preparation and CNN-SVM training process for multi-crop nutrient deficiency classification.

Figure 1 illustrates the complete workflow followed in the proposed multi-crop nutrient deficiency classification experiment. The process begins with the collection of a multi-crop leaf image dataset containing eight vegetable crops, namely ash gourd, bitter gourd, bottle gourd, cucumber, eggplant, ridge gourd, snake gourd, and tomato. The dataset consists of 36 healthy and nutrient-deficiency classes with a total of 18,000 images. After data collection, the images are organized class-wise using a folder-based dataset structure. Corrupted, duplicate, and irrelevant images are removed during the data preparation stage to improve dataset quality and reduce classification errors.

In the image preprocessing stage, all images are resized to 224 x 224 pixels and converted into RGB format to make them compatible with the selected CNN architectures. Model-specific preprocessing and batch generation are then applied before feature extraction. The dataset is divided into three subsets: 12,600 images for training, 2,700 images for validation, and 2,700 images for testing. This split ensures that the models are trained, validated, and evaluated on separate image sets.

After preprocessing, deep features are extracted using six CNN-based feature extractors: MobileNetV2, DenseNet121, ResNet50, EfficientNetB0, VGG16, and CustomCNN_Untrained. These CNN models transform the input leaf images into numerical feature vectors. The extracted feature vectors are then forwarded to the Support Vector Machine classifier. The SVM classifier learns class boundaries among the 36 nutrient-deficiency and healthy classes and performs final classification. The trained models are evaluated using accuracy, precision, recall, macro F1-score, weighted F1-score, and confusion matrix analysis. Based on the experimental results,

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EfficientNetB0 + SVM is selected as the best-performing model, achieving 87.78% accuracy and 87.74% macro F1-score.

3.3 Image Preprocessing

All images were resized to 224 x 224 pixels to match the input size required by the CNN models. The images were converted into RGB format and processed using model-specific preprocessing functions. Image generators were used to load training, validation, and testing images in batches. This preprocessing step ensured that the images were compatible with transfer learning-based CNN feature extractors.

3.4 Hybrid CNN-SVM Framework

The proposed system follows a two-stage hybrid learning approach. In the first stage, CNN models extract deep visual features from leaf images. These features represent leaf colour variation, chlorosis, necrosis, margin symptoms, texture changes, and crop-specific structural patterns. In the second stage, the extracted feature vectors are classified using an SVM classifier. This hybrid approach combines the automatic feature extraction ability of CNNs with the discriminative classification power of SVM. Since SVM performs well in high-dimensional feature spaces, it is suitable for classifying deep features extracted from CNN architectures [19], [20].

3.5 CNN Feature Extractors and Evaluation Metrics

Six CNN-based feature extractors were evaluated in this experiment. MobileNetV2 extracted 1280-dimensional features and was included because of its lightweight design [23]. DenseNet121 extracted 1024-dimensional features and was selected because dense connectivity supports feature reuse [22]. ResNet50 extracted 2048-dimensional features and was included due to its residual learning mechanism [21]. EfficientNetB0 extracted 1280-dimensional features and was evaluated because of its compound scaling strategy [24]. VGG16 extracted 512-dimensional features and was used as a classical baseline CNN architecture [25]. A CustomCNN_Untrained model was also evaluated as a baseline to compare transfer learning-based feature extraction with untrained feature extraction. The performance of each CNN-SVM model was evaluated using accuracy, macro precision, macro recall, macro F1-score, weighted precision, weighted recall, and weighted F1-score.

4. Results and Discussion

4.1 Overall Performance Comparison

The comparative performance of the six CNN-SVM models is shown in Table 2. EfficientNetB0 + SVM achieved the highest accuracy of 87.78%, with macro precision of 0.8787, macro recall of 0.8778, and macro F1-score of 0.8774. DenseNet121 + SVM achieved the second-best performance with 86.07% accuracy and macro F1-score of 0.8599. ResNet50 + SVM achieved 83.07% accuracy, while MobileNetV2 + SVM achieved 82.11% accuracy. VGG16 + SVM achieved 78.22%, and CustomCNN_Untrained + SVM achieved the lowest accuracy of 66.89%.

Table 2. Comparative performance of CNN-SVM models

Model	Accuracy (%)	Macro Precision	Macro Recall	Macro F1	Weighted F1	Feature Dim.
MobileNetV2 + SVM	82.11	0.8194	0.8211	0.8190	0.8190	1280
DenseNet121 + SVM	86.07	0.8613	0.8607	0.8599	0.8599	1024
ResNet50 + SVM	83.07	0.8297	0.8307	0.8294	0.8294	2048
EfficientNetB0 + SVM	87.78	0.8787	0.8778	0.8774	0.8774	1280

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VGG16 + SVM	78.22	0.7846	0.7822	0.7815	0.7815	512
CustomCNN_Untrained + SVM	66.89	0.6684	0.6689	0.6639	0.6639	512

4.2 Graphical Performance Comparison

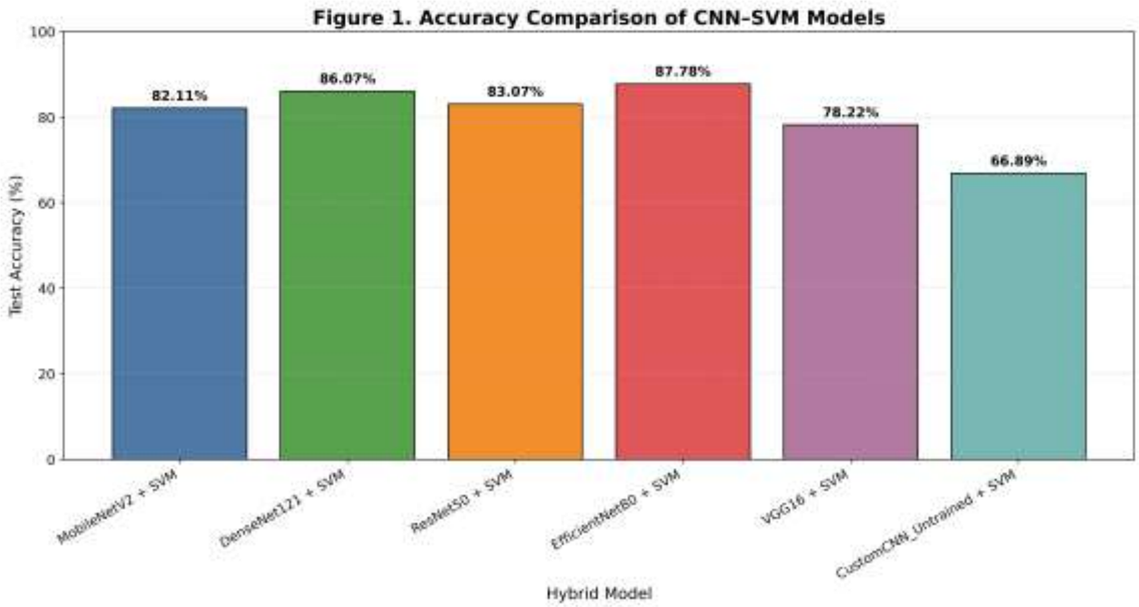

Figure 2. Accuracy comparison of CNN-SVM models for 36-class multi-crop nutrient deficiency classification.

Figure 2 presents the accuracy comparison of all evaluated CNN-SVM models. EfficientNetB0 + SVM achieved the highest accuracy, followed by DenseNet121 + SVM. The chart clearly shows that transfer learning-based feature extractors performed better than the untrained custom CNN model. The performance gap between EfficientNetB0 + SVM and CustomCNN_Untrained + SVM highlights the importance of using pre-trained deep feature extractors for nutrient deficiency classification.

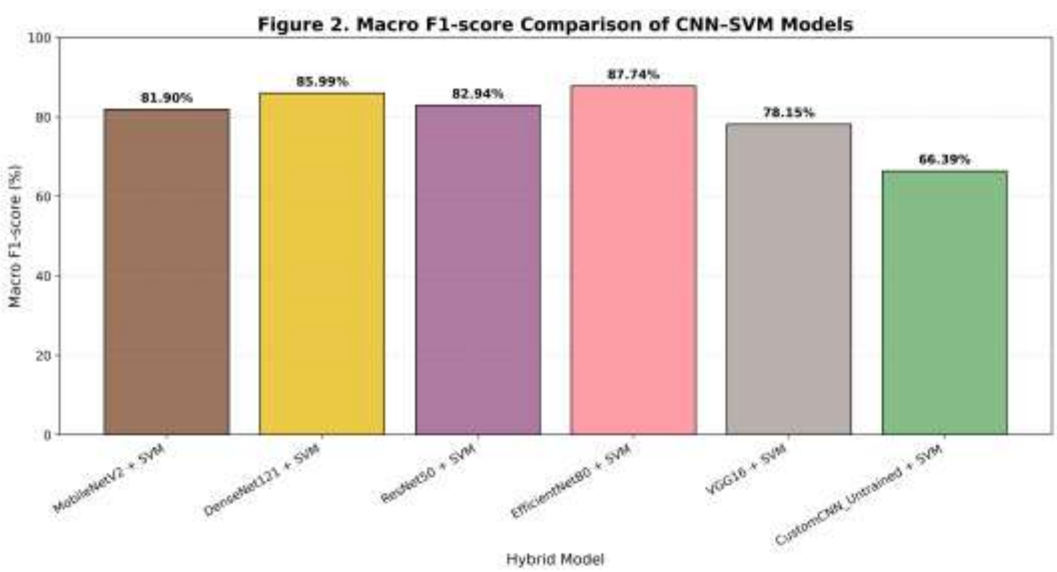

Figure 3. Macro F1-score comparison of CNN-SVM models for 36-class multi-crop nutrient deficiency classification.

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Figure 3 shows the macro F1-score comparison. Macro F1-score is important because it evaluates average class-wise performance across all 36 classes. EfficientNetB0 + SVM achieved the highest macro F1-score, indicating balanced classification performance across multiple crops and nutrient deficiency classes. DenseNet121 + SVM also showed strong class-wise performance, whereas VGG16 + SVM and CustomCNN_Untrained + SVM showed comparatively lower results.

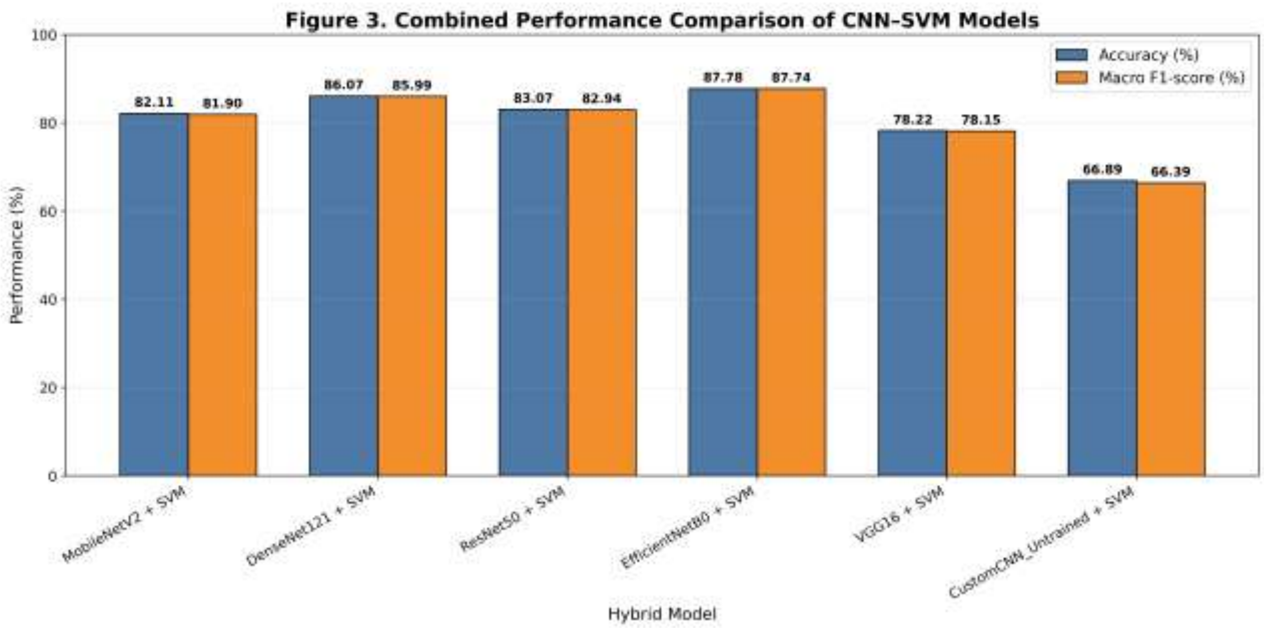

Figure 4. Combined comparison of accuracy and macro F1-score for hybrid CNN-SVM models.

Figure 4 provides a combined comparison of accuracy and macro F1-score. The combined result confirms that EfficientNetB0 + SVM consistently performed best in both overall accuracy and class-wise balanced performance. DenseNet121 + SVM was the second-best model, while CustomCNN_Untrained + SVM was the weakest model. This indicates that modern transfer learning architectures are more effective for extracting nutrient-deficiency-related leaf pattern features than older or untrained CNN models.

4.3 Interpretation of Model Performance

The results show that EfficientNetB0 + SVM was the most effective model for the present 36-class nutrient deficiency classification task. Its strong performance may be attributed to the compound scaling strategy of EfficientNet, which balances network depth, width, and resolution [24]. This design enables the model to capture both fine-grained and high-level visual features from leaf images. Such features are important for distinguishing nutrient deficiency symptoms such as chlorosis, necrosis, marginal yellowing, interveinal discoloration, and structural changes.

DenseNet121 + SVM achieved the second-best performance. DenseNet dense connectivity allows feature reuse across layers, which may help the model preserve subtle nutrient deficiency patterns [22]. This is useful because leaf symptoms may appear at different visual scales, ranging from slight colour changes to large necrotic areas. ResNet50 + SVM achieved moderate performance despite having the largest feature dimension of 2048. This suggests that feature dimension alone does not determine classification performance. Instead, the relevance and quality of extracted features are more important.

MobileNetV2 + SVM achieved competitive performance with 82.11% accuracy. Because MobileNetV2 is lightweight and computationally efficient, it may be suitable for future mobile or web-based deployment [23]. VGG16 + SVM performed lower than modern architectures, possibly because VGG16 lacks architectural

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improvements such as residual connections, dense connectivity, and compound scaling [25]. The CustomCNN_Untrained + SVM model produced the lowest performance, confirming that untrained feature extractors are not sufficient for reliable nutrient deficiency classification.

The class-wise performance of EfficientNetB0 + SVM showed that several classes achieved high precision, recall, and F1-score. Classes such as bottle_gourd__K, cucumber__healthy, ridge_gourd__N_Mg, bottle_gourd__healthy, bitter_gourd__K_Mg, and ash_gourd__K_Mg were classified effectively. However, some classes such as bitter_gourd__N and eggplant__N_K showed comparatively lower performance. This may be due to visual overlap between nitrogen deficiency and combined nutrient deficiency symptoms. Nitrogen deficiency symptoms such as yellowing and reduced greenness may resemble other deficiency patterns under different lighting and crop conditions.

5. Conclusion

This study presented a comparative hybrid CNN-SVM framework for 36-class multi-crop nutrient deficiency classification using leaf pattern analysis. Six CNN feature extractors were evaluated with SVM classification: MobileNetV2, DenseNet121, ResNet50, EfficientNetB0, VGG16, and CustomCNN_Untrained. The experiment used 12,600 training images, 2,700 validation images, and 2,700 testing images. The experimental results showed that EfficientNetB0 + SVM achieved the best performance with 87.78% accuracy, macro precision of 0.8787, macro recall of 0.8778, and macro F1-score of 0.8774. DenseNet121 + SVM achieved the second-best performance with 86.07% accuracy. The results confirm that hybrid CNN-SVM models can effectively classify nutrient deficiency symptoms across multiple vegetable crops.

The proposed approach provides a rapid, non-destructive, and cost-effective method for nutrient deficiency diagnosis. Future work will focus on field validation, dataset expansion, explainable AI using Grad-CAM, severity grading, and mobile or web-based deployment for real-time agricultural decision support.

Declarations

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Conflict of Interest

The authors declare that there is no conflict of interest.

Data Availability

The dataset used in this study was prepared for experimental research. The data may be made available from the corresponding author upon reasonable request, subject to institutional and research guidelines.

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Author Contributions

Suresh Kumar Thakur contributed to dataset preparation, model implementation, experimentation, result analysis, and manuscript writing. Dr. Anupa Sinha contributed to research supervision, methodology refinement, manuscript review, and academic guidance.

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