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CNN Models used in Agriculture- A Comprehensive Study of Nutrients and Micronutrients in Papaya Crop

Ajahar Ismailkha Pathan[1], Swati Pandey[1]

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ABSTRACT

India's economy is heavily reliant on agriculture, with a diverse array of crops grown on vast tracts of land. Fruit cultivation, especially papaya, has become more popular in recent years because of its high nutritional and financial value. To increase yield, maximize resource use and lessen reliance on chemical pesticides, modern techniques like protected cultivation and hydroponics are being used more and more. Fruit crops grown in controlled or semi-controlled environments are still susceptible to nutrient imbalances despite these developments, which can have a substantial impact on plant health, fruit quality and overall productivity. Papaya leaf nutrient deficiencies frequently show up in the early stages of growth and can result in poor fruit development and decreased yield if they are not detected in time. To support early diagnosis and better crop management, the current study focuses on creating an effective method for identifying nutrient deficiencies in papaya leaves using a deep learning (DL) framework based on transfer learning (TL). In this nutrient and micronutrient deficiency study and field work observation during year 2024 to 2026 with different climate and weather conditions done in order to tackle a new but related classification task, in the context of plant health assessment, several well-established architectures including InceptionV3, VGG19, DenseNet and Xception have been widely explored for leaf image analysis. Studies commonly utilize publicly available datasets, such as papaya leaf image repositories hosted on platforms like IEEE DataPort, to fine-tune these models for efficient feature extraction and accurate identification of nutrient and micronutrient deficiency patterns. This body of work demonstrates the growing role of transferring convolutional neural network (CNN) models in advancing automated crop monitoring and decision support systems.

Key words: Agriculture, Convolution neural network, Deep learning, Nutrients and micronutrients, Papaya plant leaves.

The fruit's skin varies in color from green to yellow. Typically, papayas are picked when their outer peel is still green with some yellow patches. A fully yellow skin usually indicates overripeness. While commonly used in desserts, papayas are also a popular addition to smoothies, yoghurt bowls and other health-focused meals due to their rich nutritional content. They are an excellent source of vitamins A and C and are known to aid digestion. Additionally, papayas are rich in antioxidants and may lower the risk of conditions like heart disease, diabetes and cancer. Their vitamin C content supports wound healing and strengthens immune function when included in a balanced diet. Beyond their use as a fruit, papayas are also effective as natural meat tenderizers, thanks to an enzyme called papain, which breaks down tough proteins in meats like beef and pork. Although the vibrant orange flesh is the most commonly consumed part, the seeds are also edible and offer a peppery flavour that can enhance various dishes (Sudhakar and Priya, 2023).

Fig 1 presents the distribution of global papaya production among the top ten producing nations in 2022 (World Population Review, 2022). India remains the leading producer, accounting for nearly half of the world's supply at 45%, with an estimated output of 5.34 million metric tons. The dominican republic follows with an 11% share and about 1.28 million metric tons. Mexico and Brazil contribute 10% and 9%, producing roughly 1.13 million and 1.11 million metric tons, respectively. Indonesia matches Brazil's presence with a 9% share and approximately 1.09 million metric tons. Nigeria provides 7% of global production, yielding close to 877,009 metric tons, while China provides 5%, producing 550,000 metric tons. The remaining countries, DR Congo (2%), Peru (1%) and Thailand (1%) contribute smaller shares, with production figures of 209,416, 176,931 and 165,605 metric tons, respectively. Overall, the chart highlights India's leading role in papaya production and shows a significant concentration of production among a few countries, with the top five accounting for more than 80% of global output Sahu *et al.* (2022).

In the period from 2023-24, Gujarat emerged as the leading papaya producing state in India, contributing 19.8% to the national output with a production volume of approximately 1.05021 million tons, cultivated over

[1]Department of Computer Science and Engineering, Oriental University, Indore-453 555, Madhya Pradesh, India.

Corresponding Author: Ajahar Ismailkha Pathan, Department of Computer Science and Engineering, Oriental University, Indore-453 555, Madhya Pradesh, India.
Email: pathan.ajaharkha@gmail.com

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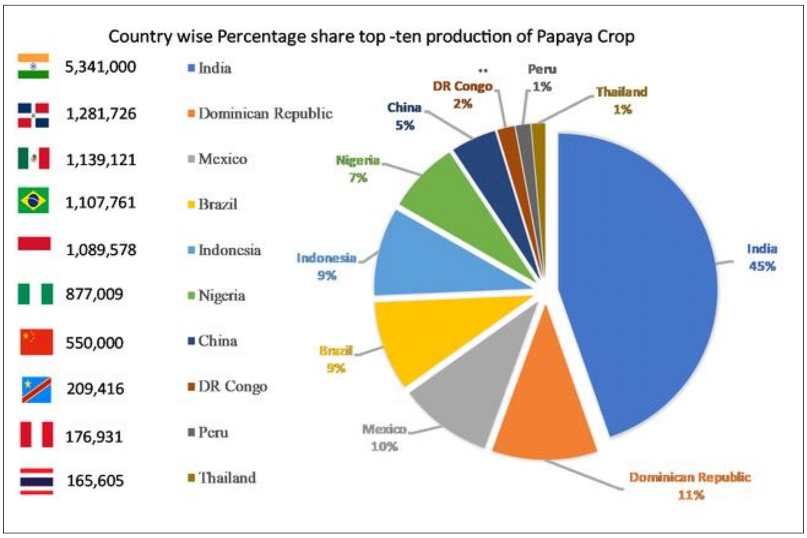

Fig 1: Country-wise top-ten production of papaya.

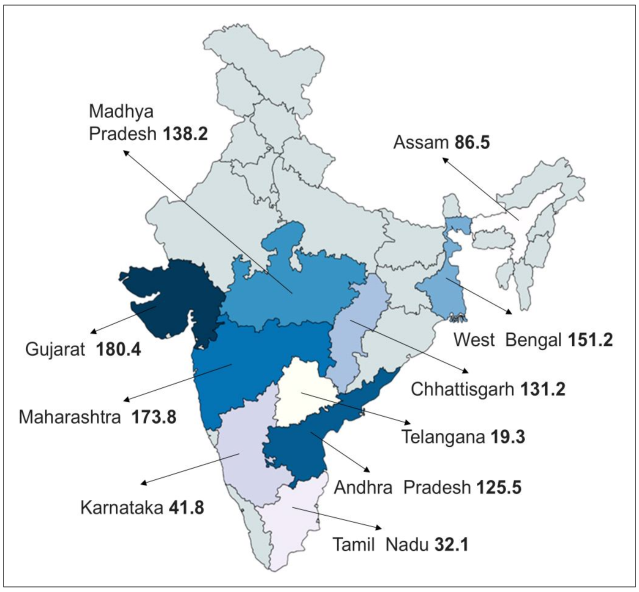

Fig 2: State-wise top-ten production of papaya.

180.4 km². Major growing regions include Ahmedabad, Jamnagar and Kheda. Andhra Pradesh followed in second place, accounting for 17.6% of the country's papaya yield with around 0.93470 million tons produced across 125.5 km^2, primarily in Anantapur, Kadapa and Kurnool. Fig 2 shows that Maharashtra holds the third position in production Sahu *et al.* (2022), generating 0.64037 million tons, about 12.1% of the national total from 173.8 km². Major papaya-growing districts in the state include Satara, Sangli, Pune, Sholapur, Nasik, Amravati and Nagpur. Tamil Nadu reported 0.21921 million tons from 32.1 km^2, primarily in Dindigul and Erode. Finally, Assam produced 0.17614 million tons, grown over 86.5 km^2, with key regions being Golaghat, Sonitpur, Udalguri, Barpeta and Kamrup Papaya production in India (DesiKheti, 2025).

Information gathering, analysis and study was carried out in the college premises, Department of Computer Science and Engineering, Oriental University, Indore-453555, Madhya Pradesh, India during November 2024 to January 2026. To study and understanding exact nutrient and micronutrient deficiency symptoms and their effect on leaves, visited the experimental field farms nearby Shahada-425409, Dist- Nandurbar, Maharashtra, India during season 2024-2025 and 2025-2026 under different conditions. The observation was recorded and image sample collected for further experiment and dataset preparation.

Nutrients and their Importance in fruit

Micronutrients, although needed only in trace amounts, are vital for the healthy growth and functioning of fruit crops. Nutrients such as iron, zinc, boron, manganese, copper and molybdenum support key physiological and biochemical activities, including enzyme functioning, chlorophyll formation, nutrient absorption and hormone regulation (Tamil Nadu Agricultural University, 2024). These elements strongly affect fruit quality by enhancing attributes like color, taste, texture and storage life. When micronutrients are lacking, crops often show poor fruit set, misshapen fruits, increased susceptibility to pests and diseases and reduced nutritional content. Ensuring an adequate and balanced supply of these nutrients is therefore essential for achieving high yields and maintaining good market quality.

The average proportion of major nutrients found in 100-grams of fresh papaya, compiled from USDA and established nutrition science sources (Olumide *et al.* 2023; USDA, 2019). The composition is approximately 88.100% water, 10.800% carbohydrates and 1.100% nutrients and micronutrients. The further distribution of 1.100% is presented in Fig 3.

The bar chart highlights the distribution of key nutrients required by fruit crops. Potassium represents the highest

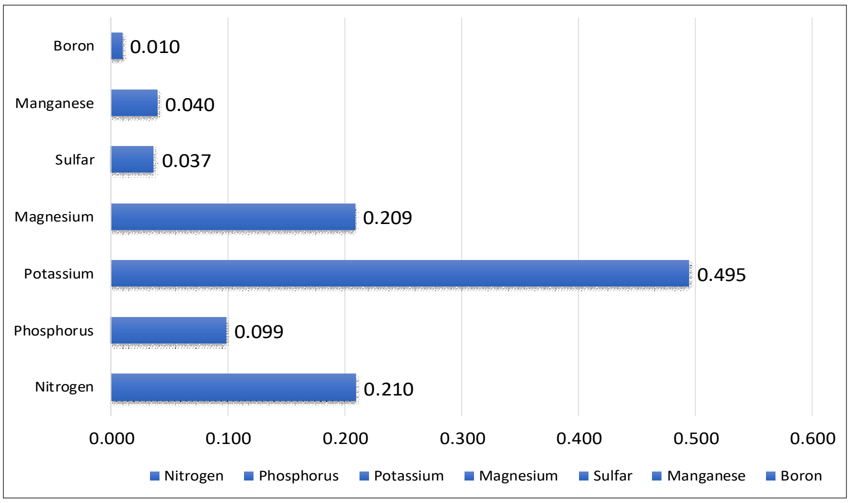

Fig 3: Breakdown of nutrient and micronutrients in papaya.

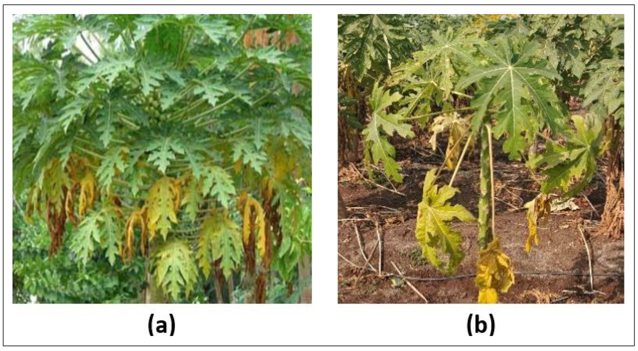

Fig 4: Papaya leaf with nitrogen deficiency symptoms.

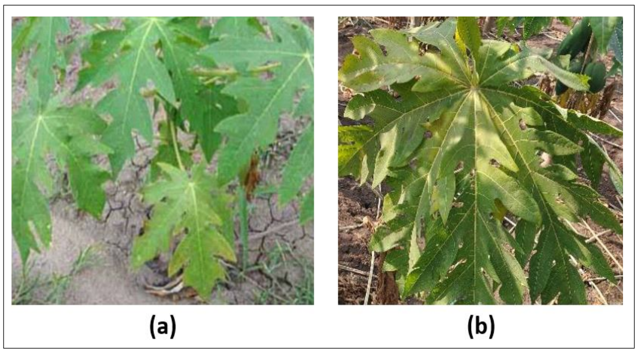

Fig 5: Papaya leaf with phosphorus deficiency symptoms.

share at 0.495%, underscoring its importance in fruit formation and plant vigor, while nitrogen follows at 0.210%. Magnesium contributes 0.209% and phosphorus 0.099%, both of which are crucial for processes such as photosynthesis and energy transfer. Manganese, sulphur and boron appear in much smaller fractions 0.040%, 0.037% and 0.010%, respectively consistent with their roles as micronutrients. Although present in minimal amounts, these elements are essential for enzyme function, nutrient utilization and structural development, reinforcing the importance of balanced nutrient management in fruit cultivation. According to USDA data, papaya contains essential micronutrients (USDA, 2019).

Method of nutrient deficiency identification

The details of nutrient deficiency visual symptoms in the papaya crop are shown below, (Jeyakumar and Balamohan, 2020; Ram *et al.*, 2023).

Nitrogen(N) deficiency causes slow growth of leaves and paler leaves, resulting in reduced leaf area and production rate. Leaf petioles are thin, short and compressed as depicted in (a) and (b) of Fig 4.

As shown in (a) and (b) of Fig 5. The deficiency of phosphorus (P) causes a blue or dark green coloration of leaves. Elder leaves become increasingly irregularly necrotic, leaf development is reduced and bordering chlorosis and early death.

Potassium (K) deficiency causes a marked reduction in growth, premature yellowing of plants and an interval with profusely smaller. Fruits are badly shaped and purple-brown coverings appear at the base of petioles as shown in (a) and (b) of Fig 6.

As depicted in (a) and (b) of Fig 7. A deficiency of magnesium (Mg) shows a green stripe around the edge and next to the midvein. Leaves turn yellow with brownish spots on the leaf edge.

As shown in (a) and (b) of Fig 8. A deficiency of sulphur (S) causes chlorosis and postponing of lime color in newly developing leaves, reduced leaf size and reduced plant growth. The leaf edges become very soft and slit easily. Finding the sulphur deficiency visually is very difficult because the symptoms are common, like those of magnesium deficiency.

As depicted in (a) and (b) of Fig 9. A deficiency of manganese (Mn) causes bordering chlorosis of early leaves, then later turns brown. Raised spots on fruits that are dim brown or black in color. Leaves give a striated presence from the boundaries.

Boron (B) deficiency leaves may become distorted and the growing point can die. The shoots are bushy, while the leaves show inward cupping and stunted growth depicted in (a) and (b) of Fig 10.

Literature review

Review strategy

This review summarizes research conducted over the past fifteen years, focusing on studies relevant to the selected topic (Shirbahadurkar, 2024). Fig 11 presents the year-wise distribution of publications from 2012 to 2025, compiled from 71 sources that include journal articles, conference papers and online materials. The trend shows a steady rise in research activity, with a noticeable peak in 2022, during which 9 studies were published, the highest in the dataset. From 2023 onward, annual publications consistently exceeded four, reflecting increasing scholarly interest in the field. Years such as 2019, 2017 and 2024 also recorded strong output with seven publications each. In contrast, 2025 shows only three entries, likely because data collection for the year is still incomplete. The earlier years 2012, 2014 and 2015 had limited contributions, each producing just one publication, marking the initial phase of research development in this domain.

Review selection criteria

The selection process for this review filtered relevant studies drawn from eight major publisher databases, resulting in a total of 71 articles. IEEE accounts for the largest portion, contributing 10 articles (16.4%). Scopus-indexed publications follow with 8 articles (13.1%). Science direct and MDPI each provide 6 articles (9.8%), while springer and elsevier contribute 5 articles apiece (8.2%). Google Scholar adds 4 articles (6.6%) and the remaining 7 articles (11.5%) come from various other Indian and international publishers.

Database sources

Fig 12 presents the percentage breakdown of the dataset sources referenced in the reviewed studies. Out of the 34 datasets identified, half (17 datasets) are proprietary or researcher-owned, making this the most common category. Custom datasets account for 17.6% (6 datasets), while plant village contributes 14.7% (5 datasets). Kaggle provides 8.8% (3 datasets) and greenhouse-based datasets represent 5.9% (2 datasets). Mendeley appears least frequently, with only one dataset (2.9%). Overall, the distribution shows a clear inclination toward using self-generated or owned datasets rather than public sources like kaggle or plant village.

Review reporting

Prince *et al.* (2024) proposed CSXAI, a lightweight model that integrates a custom-designed 2D CNN with an SVM classifier for plant disease detection across various crops, including strawberry, peach, cherry and soybean. The model was developed with the goal of offering an efficient and

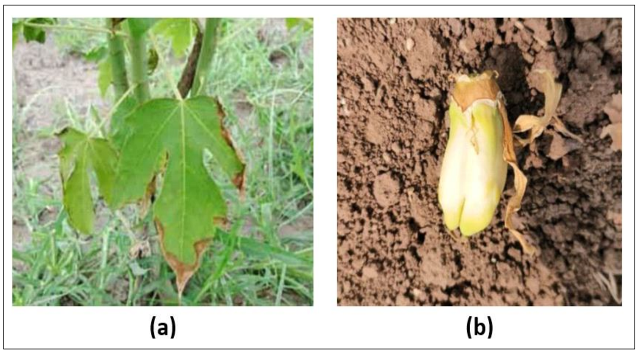

Fig 6: Papaya leaf with potassium deficiency symptoms.

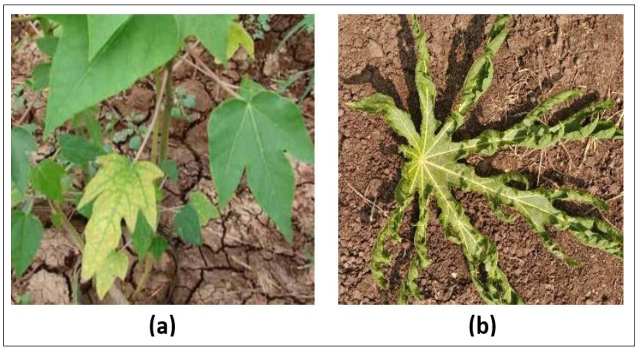

Fig 7: Papaya leaf with magnesium deficiency symptoms.

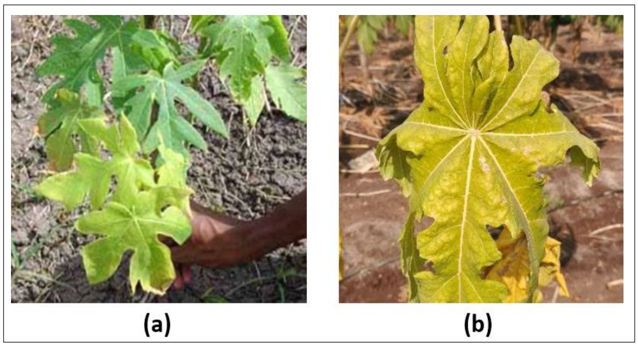

Fig 8: Papaya leaf with sulphur deficiency symptoms.

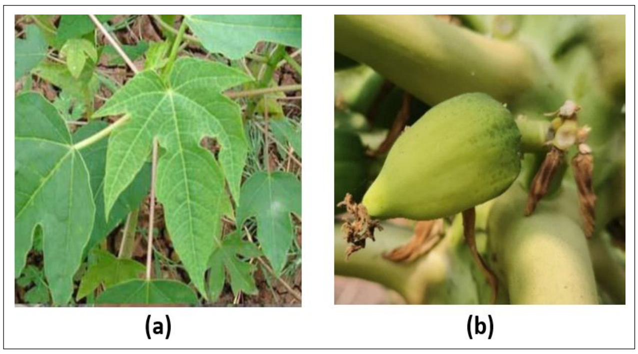

Fig 9: Papaya leaf with manganese deficiency symptoms.

accurate alternative to larger, more computationally intensive architectures. To evaluate its performance, CSXAI was benchmarked against several well-known pre-trained CNN models such as VGG16, VGG19, DenseNet, Inception, MobileNetV2 and Xception. The hybrid CNN-SVM model demonstrated an average accuracy of 99.09%, surpassing the performance of the deeper models tested, thereby highlighting its potential as a resource-efficient solution for plant disease diagnosis.

Talukder and Sarkar (2022) introduced a DL-based system designed to accurately identify nutrient deficiencies in rice plants. Their approach uses a weighted ensemble of pre-trained CNN and is trained on a Kaggle dataset consisting of 1,156 rice leaf images classified into nitrogen, phosphorus and potassium deficiency categories. To boost model performance, the authors adapted five pre-trained architectures DenseNet121, DenseNet169, DenseNet201, InceptionV3 and InceptionResNetV2 by incorporating global average pooling, dropout layers and fully connected layers. Data augmentation was applied to compensate for the limited dataset size and to reduce overfitting. Among the individual models, the enhanced DenseNet169 achieved the best accuracy at 96.66%. The final ensemble, combining InceptionV3, DenseNet169 and DenseNet201 through weighted averaging, reached an improved accuracy of 98.33%. This outperformed previously reported techniques, demonstrating the strength of ensemble learning and TL for early detection of nutrient deficiencies in rice. The authors suggest future improvements through larger datasets, hyperparameter optimization and inclusion of additional nutrient types.

Ali *et al.* (2022) introduced a DL system aimed at detecting nutrient deficiencies, specifically nitrogen, phosphorus, potassium and magnesium in grape leaves, as these deficiencies significantly influence crop productivity and quality. The team created a custom dataset consisting of 880 images collected under controlled conditions, capturing visible symptoms of the four nutrient shortages. This dataset was further expanded through data augmentation. Their method employs a CNN with several hidden layers and tuned parameters to classify leaf images into the respective deficiency categories. Performance tests, conducted using both conventional train-test splits and n-fold cross-validation, demonstrated that the model achieved an average accuracy of 96.47% on the augmented dataset. The findings highlight the strong potential of CNNs for automated nutrient deficiency detection and suggest their future use in mobile-based tools for real-time agricultural decision-making. The authors also recommend future enhancements, such as reducing model complexity to address overfitting and evaluating other DL approaches like BLSTM and reinforcement learning to improve robustness and generalization by Ali *et al.* (2022).

Sharma *et al.* (2022) introduced a DL-based approach for identifying nutrient deficiencies in rice plants using ensemble combinations of TL architectures. To overcome the computational constraints of embedded agricultural devices, the study proposes a cloud-supported diagnostic system that can be accessed through smartphones by farmers. The researchers trained six TL models-InceptionV3, ResNet152V2, Xception, DenseNet201, InceptionResNetV2 and VGG19-using augmented image datasets sourced from Kaggle and Mendeley. They then formed binary, ternary and quaternary ensemble classifiers. The ensemble groups consistently surpassed the performance of the individual TL models, with top accuracies reaching 92% on the Kaggle dataset and 100% on the Mendeley dataset. These findings show that ensemble averaging considerably enhances detection accuracy, especially when individual models exhibit lower

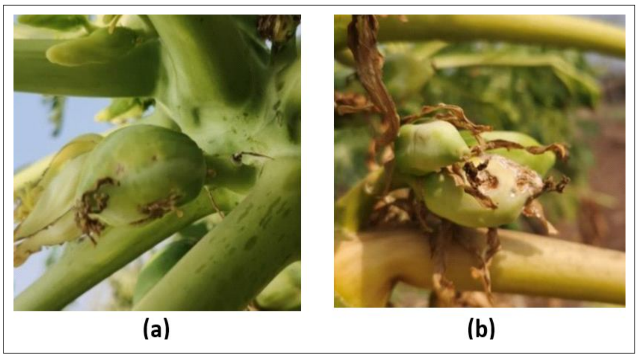

Fig 10: Papaya leaf with boron deficiency symptoms.

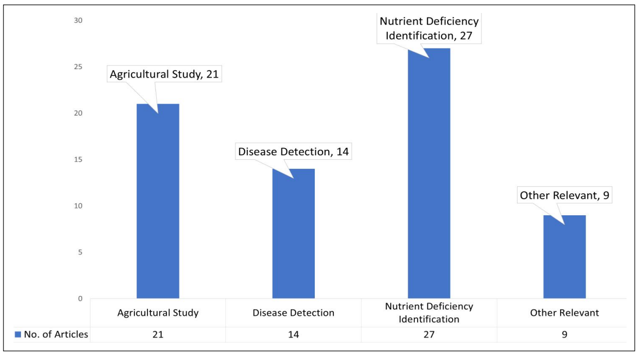

Fig 11: Work-related article distribution.

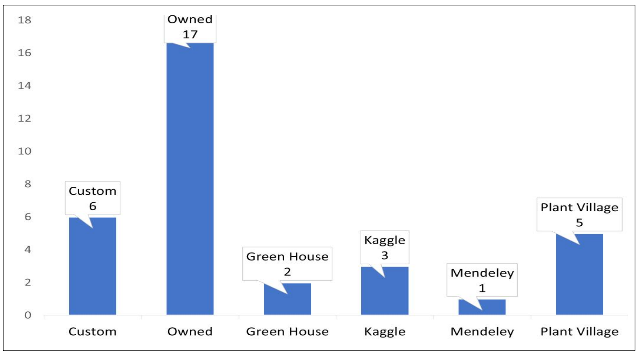

Fig 12: Distribution of review dataset sources.

reliability. Overall, the study highlights the promise of cloud-based DL solutions for smart agriculture and recommends future efforts toward expanding nutrient categories and exploring hybrid ML techniques for improved system resilience Sharma *et al.* (2022).

Ram *et al.* (2023) Several studies have demonstrated that nitrogen, phosphorus and potassium play vital roles in improving growth, yield, quality and nutrient uptake in maize. Nitrogen is essential for chlorophyll synthesis, vegetative growth and protein formation, thereby enhancing grain and straw yield. Phosphorus contributes to root development, energy transfer and reproductive growth, which ultimately improves crop productivity and nutrient absorption. Potassium supports enzyme activation, translocation of photosynthates, water regulation and stress tolerance, leading to better grain filling and crop quality. Recent findings indicated that the combined application of higher nitrogen, phosphorus and potassium levels resulted in superior yield performance and enhanced nutrient uptake in hybrid maize cultivated under South Gujarat conditions. Therefore, proper nutrient management through optimum NPK fertilization is essential for achieving sustainable maize production and improving crop quality.

(Chepuri and Ramadevi, 2025) analysed TL models such as VGG16, ResNet50, MobileNetV2, DenseNet121, ConvNeXt and conclude Inception-V3 for cotton leaf disease detection. Earlier research reported that CNN-based architectures achieved significant improvements in identifying diseases such as bacterial blight, powdery mildew, aphids, army worms and target spot with high classification accuracy. Researchers also applied image augmentation, hyperparameter tuning, Gabor filtering and hybrid meta-learning frameworks to enhance model robustness and minimize overfitting. Comparative studies indicated that Inception-V3 provides superior performance due to its efficient multi-scale feature extraction capability and computational effectiveness. The proposed Inception-V3 TL approach further improved disease classification performance by achieving an accuracy of 98.85% after hyperparameter optimization, outperforming several conventional CNN architectures. The findings confirm that DL-based cotton disease detection systems can support sustainable farming practices by enabling early diagnosis, reducing unnecessary chemical usage and improving crop quality. Therefore, the integration of TL and advanced CNN architectures offers a reliable and scalable solution for intelligent crop health monitoring in modern agriculture.

Available CNN classifications models

Several research articles discussing different machine learning (ML) models have been reviewed and these studies can be grouped based on their classification techniques. Table 1, offers a comprehensive comparative summary of available CNN models applied on different datasets, including effectiveness and accuracy. Fig 13 presents a detailed overview of this categorization.

Supervised ML models

Artificial neural networks (ANNs), first introduced in 1958 with the perceptron and later popularized in the 1980s and 1990s, are a fundamental type of ML model that relies on labelled data for training. An ANN is composed of interconnected layers of input, hidden and output where each neuron is linked through weighted connections. These networks typically use activation functions such as Sigmoid or ReLU introduce to enable learning complex patterns and non-linearity. The architecture is fully connected, that is, each neuron in one layer connects to every neuron in the next. ANNs are widely used for tasks like pattern recognition and regression due to their ability to model relationships in data effectively.

Support vector machines (SVMs), introduced in 1995, are supervised learning models primarily used for classification tasks. Unlike neural networks, SVMs do not

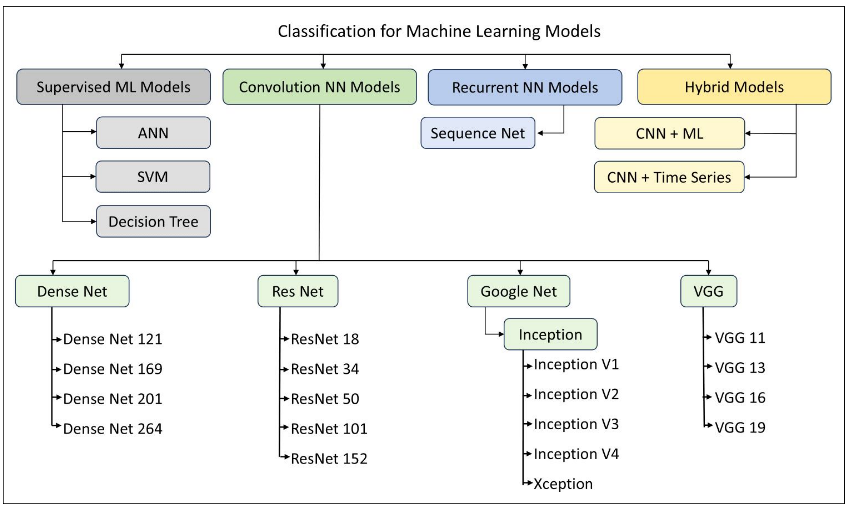

Fig 13: Classification of available models.

Table 1: Summarization of related works.

Authors	Year	Plant/crop	Dataset	No. of images	Architecture	Result perform	Deficiency detected
Xu *et al.*	2017	Multiple different plants	Own dataset of different plants	18	Genetic algorithm	82.50%	N and K
Noinongyao *et al.*	2018	Black gram	Own dataset	3000	VGG, ResNet		89.03%Ca, Fe, K, Mg and N
Leena and Saju	2019	Maize	Own dataset	100	ANN, SVM	90.00%	N, P and K
Sabri *et al.*	2020	Maize	Owned dataset of maize leaf	134	GLCM and random forest	78.35%	N, K and Mg
Yi *et al.*	2020	Sugar beet	Owned	5648	ResNet-101 and SqueezeNet	98.40%	N, P, K and Ca
Kusanur *et al.*	2021	Tomato	Greenhouse tomato leaf images	880	VGG 16+SVM		99.14%Ca + Mg
Chang *et al.*	2021	Muskmelon	Greenhouse-grown plants	624	BPNN, DCNN, LSTM	81.20%	N
Song *et al.*	2020	Wheat	Own dataset	150	BP-ANN, KNN and SBRR	79.40%	Chlorophyll
Jahagirdar and Budihal	2021	Maize	Custom dataset	1300	Inception V3		90.74%N, P and K
Shi *et al.*	2021	Cucumber	Own dataset	240	PCA and HCA		97.50%P
Sharma *et al.*	2022	Rice	Mendeley and kaggle	5790	InceptionV3, DenseNet201		100% N, P and K
Ali *et al.*	2022	Grape	Custom dataset of grape leaf	880	BLSTM	96.47%	K, N, P and Mg
Talukder and Sarkar	2022	Rice	Kaggle dataset of rice leaf	1156	Inception ResNetV2 and DenseNet201	96.66%	N, P and K
Malaisamy and Rethnaraj	2023	Groundnut (Peanut)	Augmented images of groundnut leaf	1200	CNNR-MMC	95.00%	N
Prince *et al.*	2024	Strawberry, peach, cherry	Own dataset	11524	CNN + SVM	99.09%	Mn and Mg
Pakruddin and Hemavathy	2025	Pomegranate	Own dataset	5099	PomeNetV1	99.08%	Healthy and bacterial blight diseases
Chepuri and Ramadevi	2025	Cotton	Kaggle cotton plant disease	10673	Inception-v3	98.85%	Diseases prediction

operate in layers but instead focus on identifying the optimal hyperplane that best separates data into distinct classes. By maximizing the geometric margin between different categories, SVMs enhance classification accuracy. They are particularly effective for binary classification problems and are commonly applied in areas such as text categorization and image recognition Prince *et al.* (2024).

Decision trees, popularized in 1986 with the introduction of the ID3 algorithm by Ross Quinlan, are widely used machine learning models for both classification and regression tasks. They operate using a tree-like structure where each internal node makes a decision based on a specific feature and each leaf node represents outcome or prediction. The model builds itself through recursive splitting of the dataset, typically using criteria such as information gain (entropy) or the Gini index to determine the best splits. This structure allows Decision Trees to handle non-linear, complex relationships in data while remaining relatively easy to interpret.

Convolutional neural network models

CNNs extract features from images using filters from Sharma *et al.* (2022).

DenseNet, introduced in 2017, is a CNN architecture known for its dense connectivity pattern, where each layer takes input from all preceding layers. This unique structure enhances feature reuse, improves the flow of gradients during training and increases parameter efficiency. One of the key benefits of DenseNet is its ability to mitigate the disappearing gradient problem, which commonly affects deep networks. Several versions of DenseNet have been developed, including DenseNet121, which comprises 121 layers (Patil and Ajit, 2025), as well as deeper variants like DenseNet169, DenseNet201 and DenseNet264, each offering progressively improved performance for complex image recognition tasks.

MobileNet, first introduced by Google in 2017 with the release of MobileNetV1, is a family of lightweight CNNs designed specifically for mobile and embedded devices. Its key innovation lies in the use of depth-wise separable convolutions, which significantly reduce the number of parameters and computational cost without sacrificing much accuracy Hukkeri *et al.* (2024). MobileNetV1 consists of 28 layers and approximately 4.2 million parameters. Building on this, MobileNetV2, released in 2018, introduced features like inverted residuals and linear bottle-necks to improve performance and efficiency further. In 2019, MobileNetV3 was developed by combining neural architecture search (NAS) with Net Adapt and incorporated the h-swish activation function for better accuracy and speed. The latest iteration, MobileNetV4, launched in 2020, further refined the architecture using advanced NAS techniques to optimize the model for both resource-constrained and high-performance scenarios.

AlexNet, developed by Alex Krizhevsky and introduced in 2012, gained prominence after winning the ImageNet large scale visual recognition challenge (ILSVRC). This pioneering DL model played a significant role in advancing computer vision by demonstrating the effectiveness of deep CNNs. AlexNet features five convolutional layers followed by three fully connected layers and contains around 60 million parameters. It introduced several key techniques such as ReLU activation for faster training, dropout to prevent overfitting and data augmentation to improve model generalization. Its success marked a major turning point in the adoption of DL for visual recognition tasks.

ResNet, or Residual Network, was introduced by microsoft research in 2015 and is known for its use of residual connections, also called skip connections, which help prevent vanishing gradients in very deep networks. These connections make it easier to train deep architectures and models to learn identity mappings. ResNet comes in various versions, such as ResNet18 and ResNet34, which are relatively shallow, while ResNet50 incorporates bottleneck blocks for improved efficiency and has become a standard choice in many applications Shree *et al.* (2025). For more demanding tasks, deeper versions like ResNet101 and ResNet152 offer enhanced performance by enabling even more complex feature learning.

GoogleNet, introduced in 2014 with Inception V1, is aDL architecture that brought forward the innovative concept of Inception a module structure that applies multiple convolutional filters of different sizes (1×1, 3×3 and 5×5) in parallel within the same layer. This approach allowed the network, which contains 22 layers, to efficiently capture features at various scales while keeping computational costs manageable. Subsequent versions enhanced this design: Inception V2 and V3, released in 2015, introduced factorized convolutions to further reduce complexity; Inception V4 in 2016, combined Inception modules with residual connections for improved training of deeper networks. Later in 2017, Xception, short for “Extreme Inception,” was proposed, replacing standard convolutions with depth-wise separable convolutions to increase efficiency and accuracy in large-scale image classification tasks.

InceptionV3, developed by Google, is the third version in the Inception family of DL architectures. While batch normalization was introduced in Inception V2, Inception V3 further improved performance by incorporating the concept of factorization, which reduces the number of parameters and connections without compromising accuracy (Chepuri and Ramadevi, 2025). The architecture combines multiple techniques like pooling, max pooling, dropout and fully connected layers. Its final layer uses a classifier for output prediction. Overall, the model consists of 42 layers and accepts input of size 299 × 299 pixels, making it both deep and computationally efficient.

VGG, developed by the Visual Geometry Group at the University of Oxford and introduced in 2014, is a DCNN architecture known for its simple yet effective design. It relies on stacking multiple 3×3 convolutional layers and using 2×2 max pooling for downsampling, enabling the construction of very deep networks. The different versions, VGG11, VGG13, VGG16 and VGG19 are named based on the total number of weight layers, including both convolutional and fully connected layers (Patil and Ajit, 2025). While VGG models are praised for their straightforward structure and strong performance, they are also known for being computationally intensive, which can limit their practicality in resource-constrained environments.

Recurrent neural network (RNN) models

Sequence networks, commonly represented by recurrent neural networks (RNNs), were introduced in 1986 and are designed to handle sequential data by maintaining a form of memory across time steps. This is achieved through looped connections within the network, enabling it to learn temporal patterns in data such as time series or natural language. However, basic RNNs often struggle with vanishing gradient issues during training. To overcome this, advanced variants like long short-term memory (LSTM), introduced in 1997 and gated recurrent units (GRU) were developed, offering improved capability to capture long-term dependencies in sequences.

CONCLUSION

CNN–based methods have emerged as effective tools for identifying nutrient and micronutrient deficiencies in papaya cultivation, offering accuracy, speed and scalability beyond traditional diagnostic practices. The findings reviewed indicate that DL models can significantly enhance precision agriculture, particularly when combined with enabling technologies such as remote sensing platforms, unmanned aerial systems and IoT-driven data acquisition. Despite these advances, challenges related to dataset diversity, environmental variability and the limited interpretability of deep models remain obstacles to large-scale deployment. Addressing these issues through the development of robust, transparent and adaptable architectures will be essential for practical implementation. Overall, this study highlights the growing role of CNN-driven approaches in improving crop health assessment and emphasizes their potential contribution to sustainable agricultural management and long-term food security.

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Conflict of interest

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