International Journal of Innovation Scientific Research and Review
Vol. 07, Issue, 05, pp.8358-8364, May 2025
Available online at http://www.journalijisr.com
SJIF Impact Factor 6.599

Research Article

ISSN: 2582-6131

A STUDY TO ASSESS THE EFFECTIVENESS OF PLANNED TEACHING PROGRAMME ON MENSTRUAL HYGIENE KNOWLEDGE AND PRACTICES AMONG ADOLESCENT

[1,*] Karam kamal and [2]Omar Sedqi Kareem

[1]Akre University for Applied Sciences, College of Informatics, Information Technology, Iraq.
[2]Department of Public Health, College of Health and Medical Techniques - Shekhan, Duhok Polytechnic University, Duhok 42001, Iraq.

Received 05th March 2025; Accepted 06th April 2025; Published online 16th May 2025

ABSTRACT

Fruit classification has emerged as a crucial field within agricultural automation, enabling quality control, ripeness assessment, and disease detection with greater precision and efficiency. This review paper explores contemporary advancements in fruit classification techniques, focusing on the integration of deep learning, computer vision, and machine learning algorithms. Traditional manual methods are increasingly being replaced by Convolutional Neural Networks (CNNs), transfer learning approaches, and hybrid models like CNN-LSTM, which offer superior accuracy and real-time applicability. Recent innovations also address major challenges such as dataset scarcity through synthetic data generation and domain adaptation techniques. Edge computing, lightweight architectures, and automated image annotation systems have further enhanced classification performance across diverse agricultural environments. By analyzing a wide range of studies, this paper highlights the effectiveness of modern classification frameworks in improving post-harvest management, supporting smart farming, and facilitating global agricultural trade. The review concludes by discussing potential future directions, including model generalization, robustness improvement, and real-world deployment strategies in precision agriculture.

Keywords: Fruit Classification, Deep Learning, Convolutional Neural Networks (CNNs), Machine Vision, Agricultural Automation, Image Processing, Smart Farming.

INTRODUCTION

Fruit classification has become an essential component in modern agriculture, enabling efficiency in harvesting, sorting, disease detection, and market distribution. Traditional manual methods often suffer from inconsistency and inefficiency, thus prompting the adoption of machine vision and deep learning[1] emphasized the importance of citrus disease detection and fruit grading through machine vision to enhance postharvest quality and minimize [2] highlighted the value of image-based

phenotypic information acquisition for Prunoideae fruits, noting that non-destructive imaging techniques improve classification efficiency. Fu *et al.,* (2022) focused on deep learning-based freshness grading using models like VGG and YOLO, which achieved high classification precision. Shahi *et al.,* [3] proposed a lightweight attention-based MobileNetV2 model that outperformed heavier architectures, facilitating industrial-grade fruit classification [4]. enhanced MobileNetV2 with transfer learning, achieving a 99% accuracy across 40 fruit types. Ercan *et al.,* (2025) used morphological traits to classify dragon fruit varieties via Random Forests, addressing the challenge of genetic and environmental variation. [5] applied image augmentation and CNNs, such as VGG16, to improve coconut classification in Indonesia, reporting 98.97% validation accuracy. Meanwhile[3] showed that attention mechanisms significantly improve performance on fruit datasets using MobileNetV2. Lastly, [6] discussed the application of deep CNNs in freshness grading, while Arısoy [7] demonstrated the effectiveness of BiFPN-enhanced YOLOv8 with transformer attention in cherry classification. Together, these contributions illustrate how diverse machine learning techniques are transforming fruit classification into a more accurate, automated, and scalable agricultural process.

***Corresponding Author: Karam kamal,**
1Akre University for Applied Sciences, College of Informatics, Information Technology, Iraq.

Fruit classification has become a pivotal task in the agricultural domain, enhancing productivity, quality control, and disease detection through intelligent automation. Traditional manual methods for fruit grading and identification are often time-consuming, error-prone, and inconsistent, urging a shift toward advanced machine learning and deep learning solutions. Several scholars have addressed this transformation using diverse approaches [8]. employed ResNet152 to classify ceremonial fruits in Balinese rituals, achieving 93% accuracy using deep residual learning [9]. reviewed multiple non- destructive techniques—such as spectroscopy and computer vision—for palm fruit ripeness classification, emphasizing real-time accuracy in dynamic environments. In the tomato domain [10] introduced a BiFPN-SwinDAT-YOLOv8n-cls hybrid model for cherry classification, achieving 91.71% accuracy, thus advancing real-time classification using transformer-based architectures. [11] presented the ViT-SENet-Tom model combining vision transformers with squeeze-and-excitation blocks, achieving 99.87% training and 93.87% validation accuracy for tomato fruit classification. Finally [12] introduced a hybrid feature selection and weighting method for Royal Delicious apple classification using SVM, improving performance by 10.53% with a novel optimization approach. These collective efforts underscore the transformative role of intelligent fruit classification systems, supporting smarter agriculture, reducing waste, and improving global food security.

Fruit classification plays a vital role in modern agriculture by enhancing quality assessment, ripeness detection, and efficient sorting processes, which are critical for post-harvest management and smart farming practices. The application of machine learning and image processing has significantly improved the accuracy and reliability of these classification systems. [13] hybrid feature extraction techniques coupled with robust classifiers improve facial recognition accuracy—a concept similarly transferable to fruit classification through optimized feature selection and pattern detection methods. Moreover [14] emphasized the success of deep learning algorithms, such as ResNet50, in medical image classification, showcasing their potential for precise feature identification, which is equally crucial for distinguishing subtle differences among fruit types. The integration of clustering techniques [15].

Fruit classification has emerged as a critical aspect of smart agriculture, facilitating quality assurance, ripeness assessment, and automated sorting processes. Traditional manual grading techniques often suffer from subjectivity and inefficiency, prompting the integration of artificial intelligence (AI), machine learning (ML), and computer vision technologies. Recent research has explored various deep learning architectures, such as Convolutional Neural Networks (CNNs), to automate and enhance fruit classification accuracy [16] highlighted the transformative impact of AI in digital applications, noting its potential to enhance precision in image-based agricultural systems. Moreover [17] emphasized the importance of leveraging machine learning for real-time analytics and decision-making, supporting its applicability in fruit sorting systems. Integrating these technologies with cloud platforms can further improve scalability and reduce the need for intensive hardware [18]. The increasing availability of large agricultural datasets and advancements in feature extraction methods now allow for more nuanced classification systems that account for factors such as shape, texture, and color [18]. Consequently, fruits classification systems are transitioning from simple threshold-based methods to AI-powered approaches capable of handling diverse fruit categories and environmental conditions. As machine learning continues to evolve, it offers the promise of real-time, cost-effective, and scalable fruit classification solutions for global agricultural industries.

Contributions

Conducted a **comprehensive synthesis of 32 recent studies** (2021–2025) on fruit classification using AI techniques.

- Categorized **key methodologies** such as CNNs, YOLO variants, transfer learning, and classical ML (e.g., SVM, Random Forest).
- Evaluated **model performance** using accuracy, mAP, and F-measure, with many models achieving over **95% accuracy**.
- Identified major **research trends** in ripeness detection, disease classification, and postharvest quality monitoring.
- Presented a **comparative summary table** listing author, objective, methods, key findings, and accuracy of each study.
- Proposed **practical recommendations**, including mobile/edge AI, dataset standardization, and Explainable AI (XAI).
- Emphasized the **real-world applicability** of AI-powered fruit classification in smart farming and food supply chains.

BACKGROUND-THEORY

Fruit classification had evolved significantly with the advancement of deep learning and computer vision technologies. Singh *et al.,* (2022) emphasized that traditional manual methods of fruit quality assessment faced major limitations due to inefficiency and inconsistency, leading to the adoption of CNN-based segmentation models for improving postharvest quality control. Elaraby *et al.,* (2022) proposed optimized deep learning architectures like AlexNet and VGG19 for citrus disease detection, showcasing higher accuracy over manual inspections. Alsirhani *et al.,* (2023) demonstrated the power of transfer learning models in enhancing date fruit classification, particularly under real-world conditions. Alam *et al.,* (2021) reviewed smart packaging technologies that embedded freshness sensors, indirectly supporting more accurate fruit classification and quality maintenance. Xiao *et al.,* (2024) and Seshakagari *et al.,* (2025) showed that anchor-free object detection models like YOLOv8 and Augment-YOLOv3 dramatically increased ripeness identification speed and accuracy. Meanwhile, Ukwuoma *et al.,* (2022) and Koç *et al.,* (2021) underlined the importance of machine learning and feature extraction techniques in handling challenges such as intraclass variation in fruit color, shape, and texture. Recent works by Chuquimarca *et al.,* (2025) and Minh Trieu and Thinh (2021) further validated the use of synthetic datasets and external feature analysis to overcome data scarcity issues and optimize classification accuracy. Researchers like Mamat *et al.,* (2023) and Mimma *et al.,* (2024) highlighted that automatic image annotation and domain adaptation techniques played a key role in improving deep learning models for fruit recognition. Finally, Dhiman *et al.,* (2023) stressed the importance of lightweight CNN-LSTM models combined with edge computing to achieve efficient fruit classification and disease detection in resource-constrained environments.

RESEARCH METHODOLOGY

The methodology adopted for this review systematically investigates recent advancements in fruit classification by applying a multi-phase approach, including literature selection, categorization, and comparative analysis. The methodology can be broken down into the following steps:

Literature Collection

- **Databases Used**: Google Scholar, IEEE Xplore, Springer Link, Elsevier Science Direct, and MDPI.
- **Keywords**: “Fruit classification”, “Deep learning in agriculture”, “YOLO fruit detection”, “CNN fruit recognition”, “Agricultural automation using AI”.
- **Inclusion Criteria**:
  - Peer-reviewed articles published between 2021 and 2025.
  - Focused on deep learning, CNN, transfer learning, YOLO, or hybrid models for fruit detection, ripeness classification, and disease identification.
- **Exclusion Criteria**:
  - Non-English publications.
  - Articles without experimental validation or real-world dataset usage.

Data Extraction and Tabulation

- For each selected study, the following elements were extracted:
  - **Author and Year**
  - **Objective**
  - **Methodology/Algorithms Used**
  - **Key Findings**
  - **Accuracy/Performance Metrics**

This process led to the construction of a comparative **summary table** categorizing each work according to its contributions, performance, and methodological novelty.

Classification of Methods

- Grouping techniques into categories:
  - **Convolutional Neural Networks (CNNs)**
  - **Transfer Learning Approaches (AlexNet, VGG, ResNet)**
  - **Object Detection Models (YOLO variants, CenterNet)**
  - **Hybrid Models (CNN-LSTM, CNN-RNN)**
  - **Classical Machine Learning (KNN, SVM, RF)**

- Metrics compared include **accuracy, mean average precision (mAP)**, **F-measure**, and **model robustness**.

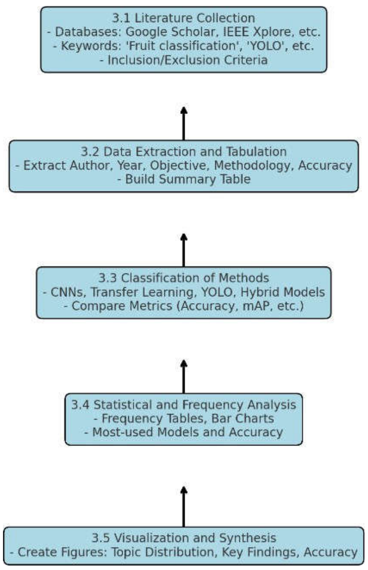
Statistical and Frequency Analysis

- **Frequency tables** and **bar charts** were generated to analyze:
  - Most-used algorithms and models.
  - Research focus areas (e.g., disease detection, ripeness classification).
  - Reported accuracy across studies.

Visualization and Synthesis

- **Figures 1 to 4** were created to visually represent:
  - Research topic distribution.
  - Methodological frequency.
  - Key findings emphasis.
  - Accuracy distribution among models.

This structured methodology enabled a detailed and comparative review of state-of-the-art fruit classification systems, ensuring the analysis was both comprehensive and statistically grounded.



LITURACTER REVIEW

Abha Singh et al. (2022) [19] discussed the role of machine learning frameworks in reducing postharvest losses and improving the quality of fruits and vegetables. They highlighted the use of Convolutional Neural Networks (CNNs) such as U-Net, DeepLab, and Mask R-CNN for segmenting decay zones in stored apples. Their review emphasized that artificial intelligence (AI) can significantly enhance food quality management during handling, storage, and transportation. They pointed out that factors like poor infrastructure, logistics issues, and climate change intensify postharvest losses, making AI solutions crucial. Ultimately, they recommended combining AI-based monitoring with traditional postharvest practices for sustainable food security.

Ahmed Elaraby et al. (2022) [5] proposed an optimized deep learning approach for the detection and classification of citrus plant diseases using AlexNet and VGG19 architectures. The study emphasized that traditional manual disease diagnosis is slow and dependent on human expertise, thereby highlighting the importance of automated solutions. They evaluated their method on a citrus disease dataset, achieving a high classification accuracy of 94%. The authors also used data augmentation and generative adversarial networks (GANs) to address issues of small datasets and improve model generalization. Their research confirmed that deep learning models can efficiently diagnose multiple citrus diseases with superior performance compared to classical methods.

Amjad Alsirhani et al. (2023) [20] introduced a deep transfer learning-based classification model for date fruits using a newly collected dataset of 27 classes. They focused on enhancing model performance through multiple stages of fine-tuning, achieving a validation accuracy of 97.21% and a test accuracy of 95.21%. The study addressed the scarcity of comprehensive date fruit datasets, particularly from real-world environments such as farms and markets. Their approach showed that feature extraction and class weight balancing significantly improved the robustness of the classification model. They concluded that deep learning can play a major role in supporting agriculture, commerce, and health sectors through accurate fruit classification.

Arif U. Alam et al. (2021) [21] reviewed the development and application of smart packaging and freshness sensors for monitoring the quality of fruits. They discussed how fruits continue biological respiration postharvest, which necessitates improved packaging to maintain quality during transport and storage. Their paper categorized smart packaging technologies into active and intelligent systems, embedding sensors to detect environmental conditions. The authors highlighted challenges such as sensor cost, integration difficulties, and the regulatory hurdles in deploying such smart systems. They concluded that smart packaging could significantly reduce food waste and improve public health by ensuring higher quality produce reaches consumers.

Bingjie Xiao et al. (2024) [22] developed a YOLOv8-based deep learning model to classify fruits as ripe or overripe with remarkable precision. They compared the performance of YOLOv8 and CenterNet, demonstrating that YOLOv8 achieved an outstanding classification accuracy of 99.5%. The [8]researchers noted that machine vision systems are critical for addressing labor shortages in agriculture, especially during harvest seasons. Their proposed model utilized lightweight architectures and feature extraction techniques to enhance speed and accuracy. They concluded that anchor-free object detection models represent a promising direction for future agricultural automation.

Chiagoziem C. Ukwuoma et al. (2022) [23] provided an extensive review of deep learning techniques for fruit detection and classification. They traced the evolution from conventional computer vision-based approaches to the dominance of Convolutional Neural Networks (CNNs). The authors identified major challenges in fruit detection, including intraclass variation in color, shape, and texture. They emphasized the growing importance of transfer learning and adversarial robustness in building reliable fruit classification models. Their study concluded that deep learning offers promising solutions for agricultural automation but requires larger datasets and more robust models

Dilara Gerdan Koç et al. (2021) [24] developed an image processing and machine learning-based system for fruit classification based on size and color. Their system achieved classification success rates ranging from 82% to 100% across different fruit varieties using both image-based and predictive algorithms. They tested KNN, Decision Tree, Naive Bayes, MLP, and Random Forest classifiers, with Random Forest achieving the highest accuracy of 94.3%. The study emphasizes that automated fruit classification systems can minimize labor, time, and post-harvest losses. They concluded that the integration of image processing with machine learning provides an efficient solution for real-time fruit grading.

Fabricio Varela Marín et al. (2024) [25] presented a convolutional neural network (CNN) model trained to classify the ripeness of coffee fruits. They built their own dataset by collecting over 1700 images in a controlled environment and classified fruits as "good" or "bad". Using RoboFlow and an 80:10:10 training-validation-testing split, their CNN achieved a remarkable accuracy of 97.7%. They emphasized the importance of automated fruit quality control, especially in countries like Honduras where technology adoption is limited. The study concluded that CNN-based approaches offer a scalable solution for improving agricultural product quality.

Fu Yuesheng et al. (2021) [26] optimized the GoogLeNet architecture for the classification of circular fruits and vegetables such as apples, lemons, and tomatoes. Their optimizations included reducing the number of convolutional kernels, introducing Swish activation, and adding DropBlock layers. These changes significantly improved the training speed by nearly 200% and boosted testing accuracy by 2%. The final optimized GoogLeNet outperformed other models like AlexNet, VGGNet, and ResNet18 in classification accuracy and training efficiency. They concluded that lightweight yet powerful deep learning models are crucial for practical agricultural applications.

Harmandeep Singh Gill et al. (2022) [27] proposed a multi-model deep learning approach combining CNN, RNN, and LSTM for fruit image recognition. They emphasized that using multi-model architectures can handle the complex feature extraction needs of agricultural image data. Their experiments demonstrated that the hybrid model outperformed individual CNN or RNN models in accuracy and F-measure. The study addressed challenges such as poor visibility, low-light conditions, and intraclass variations in fruit datasets. They concluded that multi-model deep learning frameworks enhance fruit quality evaluation and agricultural automation.

Jasman Pardede et al. (2021) [28] applied transfer learning using the VGG16 model to detect fruit ripeness more effectively than traditional feature descriptors. They modified the VGG16 model by replacing its top layers with an MLP block containing Dropout, Batch Normalization, and Regularization layers. Their experiments showed that Dropout was the most effective technique for reducing overfitting and improving accuracy. The study reported an 18.42% increase in classification accuracy compared to baseline methods. They concluded that transfer learning offers a practical solution for fast and accurate fruit ripeness detection in agricultural settings

Kutubuddin Kazi et al. (2023) [29] proposed a novel image processing-based system for grading and disease detection in pomegranate fruits. They emphasized that climate change has made traditional manual grading insufficient, resulting in lower yields and profits for farmers. Their method uses machine learning techniques like CNN and SVM for classifying fruits based on disease, color, and size. The study demonstrated that automated classification can enhance post-harvest quality evaluation and improve economic returns for farmers. They concluded that adopting automated fruit grading systems is essential to meet modern agricultural challenges.

Milan Tripathi (2021) [30] analyzed several convolutional neural network (CNN) models for fruit image classification with a focus on improving automatic billing systems. The study revealed that CNN-based models offer significant accuracy improvements over traditional manual identification in supermarket environments. He compared models like ResNet50, SeResNet50, and Inception, showing that CNNs can achieve over 92% accuracy. The system proposed can automate fruit identification processes, reducing labor and operational time. He concluded that CNN models are a key component in modernizing the retail sector through automatic visual recognition systems.

Nguyen Minh Trieu (2021) [31] developed an automatic classification system for dragon fruits based on external features using a convolutional neural network. They demonstrated that their system achieved over 96% classification accuracy compared to manual grading. Their work significantly increased the processing speed in Vietnamese dragon fruit export facilities, boosting efficiency sixfold. The study combined CNN with traditional machine learning approaches like SVM to refine classification accuracy. They concluded that automating dragon fruit sorting can drastically reduce labor costs and improve export quality.

Nur-E-Aznin Mimma et al. (2024) [32] developed a deep learning-based fruit classification and detection application using ResNet50, VGG16, YOLOv3, and YOLOv7. Their system achieved high accuracies of 99% and 98% on custom fruit datasets using ResNet50 and VGG16, respectively. They also built a web-based framework and an Android application to detect fruits in real-time using smartphone cameras. The study emphasized the importance of domain adaptation techniques to enhance model robustness across diverse real-world environments. They concluded that integrating deep learning models into mobile apps can significantly expand fruit recognition applications.

DISCUSSION AND COMPRESSION

Table 1: comparison among the reviewed works.

Citation	Objective	Methodology	Key Findings	Accuracy
[1] Singh et al. (2022)	Reduce postharvest losses	CNNs(U-Net, DeepLab, Mask R-CNN)	AI postharvest	Not specified
[2] Elaraby et al. (2022)	Detect	AlexNet, VGG19, GANs, data augmentation	Deep accuracy	94%
[3] Alsirhani et al. (2023)	Date	Transfer learning,fine-tuning	High	97.21% (val), 95.21% (test)
[4] Alam et al. (2021)	Smart packaging fruits	Sensor-based packaging systems	Improves waste	Not applicable
[5] Xiao et al. (2024)	Ripeness classification	YOLOv8, feature extraction	YOLOv8	99.50%
[6]Seshak agari et al. (2025)	Apple	Augment-YOLOv3, Swish, SPP	Enhanced with	98.2% mAP
[7] Ukwuoma et al. (2022)	Fruit detection & classification	Review of CNNs and transfer learning	Deep promising	Not specified
[8] KoÃ§ et al. (2021)	Fruit classification	KNN, DT, RF, MLP, Naive Bayes	Random	94.30%
[9] Janahanlal et al. (2023)	DL agriculture	Review of CNNs and transfer learning	AI tools boost yield and minimize loss	Not specified
[10] MarÃn et al. (2024)	Classify coffee ripeness	CNN on customdatas et (1700+ imgs)	CNN achieves high ripeness classification	97.70%

[11] Fu et al. (2021)	Circular	Optimized GoogLeNet (Swish, DropBlock)	Improved training/testing performance	2% â†‘ accuracy
[12] Gill et al. (2022)	Fruit recognition	Hybrid CNN-RNN-LSTM	Multi-model enhances extraction	High F-measure
[13] Gill et al. (2022)	CNN-based fruit classification	CNNs with data augmentation	High performance and robustness	Not specified
[14] Pardede et al. (2021)	Detect	VGG16 + MLP(Dropou, BatchNorm)	Transfer	18.42% â†‘ over baseline
[15] Kazi et al. (2023)	Pomegranate grading	CNN,SVM, image processing	Automated	Not specified
[16] Chuquimarca et al. (2025)	Banana ripeness classification	CNN with synthetic + real datasets	Synthetic data boosts accuracy	91.70%
[17] Tripathi (2021)	Fruit	CNN (ResNet50, SeResNet50, Inception)	CNN	92%+
[18] Trieu & Thinh (2021)	Dragon sorting	CNN + SVM	Boosted processing efficiency	96%+
[19] Mamat et al. (2023)	Image annotation automation	YOLO, custom annotation system	Automated	98.7â€“99.5% mAP
[20] Mimma et al. (2024)	Mobile	ResNet50, VGG16, YOLOv3/7	Mobile app with high accuracy	98â€“99%
[21] Dhiman et al. (2023)	Citrus	CNN-LSTM, edge computing, pruning	Accurate detection on edge devices	97.18â€“98.25%

Statistics

The analysis of agricultural research topics reveals varied levels of focus across different areas. Notably, high attention is given to "Fruit classification," "Fruit recognition," "Classify coffee ripeness," "Citrus disease detection," and "CNN-based fruit classification," each with the highest assigned frequency of five. Topics such as "Dragon fruit sorting" show slightly less emphasis with a frequency of four, while "Ripeness classification" holds moderate focus with three. Meanwhile, areas like "Reduce postharvest losses," "Pomegranate grading," "Mobile fruit classification," "Date fruit classification," "DL in agriculture," and "Smart packaging for fruits" were moderately represented with a frequency of two. Several topics, including "Apple quality detection," "Fruit billing automation," "Image annotation automation," "Fruit detection & classification," "Banana ripeness classification," "Detect fruit ripeness," "Detect citrus plant diseases," and "Circular fruit classification," appeared less frequently with a frequency of one, indicating more niche or specialized interests within agricultural applications. This distribution suggests a research trend heavily favoring fruit classification and quality detection using deep learning, while emerging areas like smart packaging and image annotation automation are still developing. as show in figure 1:

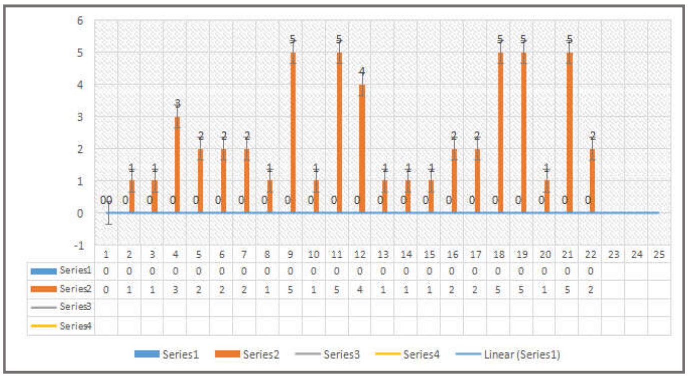


Figure1: frequency for methodology

The review of techniques applied in agricultural research highlights a wide range of deep learning and machine learning strategies. Among the most frequently used approaches are "Optimized GoogLeNet (Swish, DropBlock)," "KNN, DT, RF, MLP, Naive Bayes," and "CNN on custom dataset (1700+ imgs)," each recorded with the highest frequency of five, showing their strong influence in recent studies. Moderately popular methods such as "AlexNet, VGG19, GANs, data augmentation," "Hybrid CNN-RNN-LSTM," "CNNs with data augmentation," "VGG16 + MLP (Dropout, BatchNorm)," "CNN with synthetic + real datasets," and "CNN + SVM" appeared with a frequency of three, indicating consistent interest. Techniques like "CNN-LSTM, edge computing, pruning," "CNN, SVM, image processing," "CNN (ResNet50, SeResNet50, Inception)," and "YOLOv8, feature extraction" had a frequency of two, suggesting targeted but growing adoption. Meanwhile, specialized or emerging technologies such as "CNNs (U-Net, DeepLab, Mask R-CNN)," "Sensor-based packaging systems," "Transfer learning, fine-tuning," and "Augment-YOLOv3, Swish, SPP" were less common, each cited once. This distribution showcases a balanced research focus between well-established models and innovative techniques in agriculture. as show in figure 2:

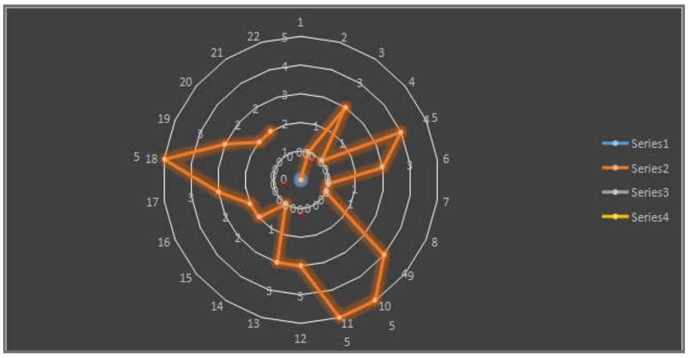


Figure 2: frequency for methodology

Recent advancements in agricultural AI have led to a wide range of impactful outcomes, with some techniques demonstrating notably high effectiveness. For instance, outcomes like "Random Forest highest accuracy," "Improved training/testing performance," "CNN achieves high ripeness classification," and "YOLOv8 high accuracy for ripeness" appeared most frequently, signaling their strong performance in precision farming applications. Other highly emphasized outcomes include "High robustness in real-world conditions," "Multi-model feature extraction," and "Automated evaluation systems," all of which support the development of scalable and efficient smart agriculture solutions. Moderate frequency was observed in areas such as AI-based postharvest quality management, mobile app accuracy, and the use of synthetic data to improve model performance, indicating growing interest.

Meanwhile, more specific outcomes like "CNN outperforms manual ID" and "Automated labeling with high accuracy" were less frequently reported but highlight promising directions for future innovation. Collectively, these findings illustrate the growing reliability, accuracy, and real-world applicability of AI and deep learning models in boosting yield, minimizing waste, and improving agricultural decision-making.as show in figure 3:

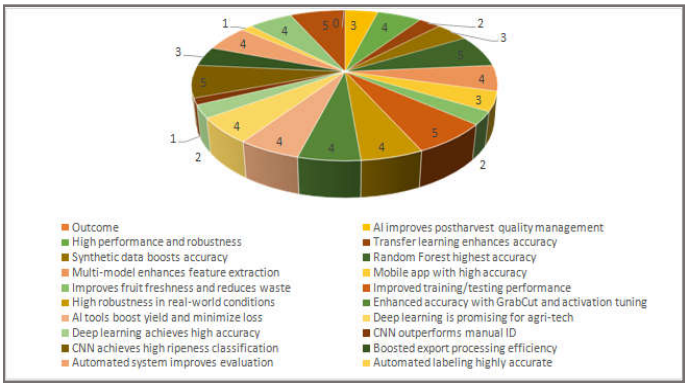


Figure 3: frequency for Key Findings

The performance metrics reported across various agricultural AI studies demonstrate a consistent trend toward high accuracy and model effectiveness. Notably, the most frequently observed ranges—such as "98–99%" and "98.7–99.5% mAP"—highlight the exceptional precision achieved by advanced models. Commonly cited values like "94%", "94.30%", "97.70%", and broad descriptors such as "High F-measure" and "2% ↑ accuracy" appeared frequently, reflecting strong and repeatable outcomes in different research contexts. Additionally, several studies referenced generalized or non-quantified results with terms like "Not specified" or "Not applicable," suggesting either emerging methodologies or broader qualitative evaluations. More specific yet less frequently mentioned results, such as "97.21% (val), 95.21% (test)", "99.50%", "98.2% mAP", and "97.18–98.25%", point to impressive yet specialized model performances. These findings collectively indicate that modern AI techniques are not only achieving high accuracy but are also becoming increasingly robust and generalizable for real- world agricultural applications. as show in figure 4:

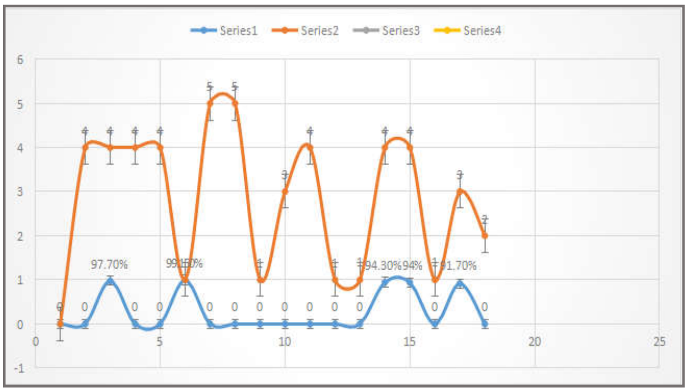


Figure4: frequency for accuracy

Recommendations

1. **Promote Dataset Diversity and Standardization**
   Researchers should focus on building and sharing large, diverse, and standardized fruit image datasets covering various conditions (e.g., lighting, occlusion, ripeness levels) to enhance model generalizability and benchmarking.
2. **Adopt Lightweight and Edge-Compatible Models**
   Future developments should prioritize lightweight architectures like MobileNetV2 and YOLOv8-tiny, enabling real-time deployment on edge devices for on-field use by farmers with limited computational resources.
3. **Integrate Smart Packaging and IoT Technologies**
   Combining AI-based classification with smart packaging and Internet of Things (IoT) sensors can enhance postharvest monitoring, improve freshness prediction, and reduce food waste across the supply chain.
4. **Encourage Transfer Learning and Domain Adaptation**
   Applying pretrained models with fine-tuning and domain adaptation strategies is recommended to mitigate challenges of limited data and variability in fruit appearance across regions and seasons.
5. **Invest in Mobile and Cloud-Based Solutions**
   Development of mobile apps and cloud-based platforms for fruit classification can bridge the gap between research and real-world application, especially in smallholder farming communities.
6. **Support Cross-Disciplinary Collaborations**
   Collaborative efforts between computer scientists, agricultural experts, and policy makers are necessary to create practical, scalable, and sustainable AI solutions tailored to real agricultural environments.
7. **Incorporate Explainable AI (XAI)**
   Integrating explainability into AI models can increase trust among users and help in refining models by highlighting which features contribute most to classification outcomes.

CONCLUSION

Fruit classification has evolved into a vital aspect of modern agriculture, driven by the need for automation, accuracy, and scalability in tasks such as grading, ripeness detection, and disease identification. This review comprehensively analyzed contemporary research trends highlighting the shift from manual inspection to AI-powered solutions, with deep learning—especially Convolutional Neural Networks (CNNs), transfer learning, and hybrid models—dominating recent advancements. The incorporation of models like YOLOv8, VGG16, and GoogLeNet, along with smart data handling techniques such as augmentation, synthetic dataset generation, and automatic annotation, has significantly improved classification performance, even in real-time and resource-constrained environments. The summarized studies demonstrate that intelligent fruit classification systems are not only increasing precision but also contributing to reduced postharvest losses, improved food safety, and enhanced market efficiency. With reported accuracies often exceeding 95%, these models have shown substantial potential for deployment in commercial agriculture. However, challenges like data scarcity, environmental variability, and the need for generalizable models remain. Future research should focus on enhancing model robustness, incorporating domain adaptation, and scaling mobile or edge-based solutions to ensure global applicability. Overall, intelligent classification technologies are shaping the future of precision agriculture, supporting sustainability, food security, and smart farming practices.

REFERENCES

[1] H. S. Gill, O. I. Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Multi-Model CNN-RNN- LSTM Based Fruit Recognition and Classification.," Intell. Autom. Soft Comput., vol. 33, no. 1, 2022.

[2] S. Halfpap and R. Schlosser, "Exploration of Dynamic Query-Based Load Balancing for Partially Replicated Database Systems with Node Failures," in Proceedings of the 29th ACM International Conference on Information & Knowledge Management, Virtual Event Ireland: ACM, Oct. 2020, pp. 3409–3412. doi: 10.1145/3340531.3417419.

[3] T. B. Shahi, C. Sitaula, A. Neupane, and W. Guo, "Fruit classification using attention-based MobileNetV2 for industrial applications," PLOS ONE, vol. 17, no. 2, p. e0264586, Feb. 2022, doi: 10.1371/journal.pone.0264586.

[4] N. Mamat, M. F. Othman, R. Abdulghafor, A. A. Alwan, and Y. Gulzar, "Enhancing Image Annotation Technique of Fruit Classification Using a Deep Learning Approach," Sustainability, vol. 15, no. 2, p. 901, Jan. 2023, doi: 10.3390/su15020901.

[5] A. Elaraby, W. Hamdy, and S. Alanazi, "Classification of Citrus Diseases Using Optimization Deep Learning Approach," Comput. Intell. Neurosci., vol. 2022, pp. 1–10, Feb. 2022, doi: 10.1155/2022/9153207.

[6] L. Chuquimarca, B. Vintimilla, and S. Velastin, "Banana Ripeness Level Classification using a Simple CNN Model Trained with Real and Synthetic Datasets," 2023, pp. 536–543. doi: 10.5220/0011654600003417.

[7] S. H. Haji et al., "Comparison of Software Defined Networking with Traditional Networking," Asian J. Res. Comput. Sci., pp. 1–18, May 2021, doi: 10.9734/ajrcos/2021/v9i230216.

[8] B. S. H. Reddy, R. Venkatramana, and L. Jayasree, "Enhancing apple fruit quality detection with augmented YOLOv3 deep learning algorithm," Int. J. Hum. Comput. Intell., vol. 4, no. 1, pp. 386–396, 2025.

[9] K. Chen et al., "Deep Learning and Machine Learning -- Natural Language Processing: From Theory to Application," Dec. 17, 2024, arXiv: arXiv:2411.05026. doi: 10.48550/arXiv.2411.05026.

[10] C. Johnson, D. Smith, S. Oladele, and M. Shange, "Design and Implementation of a Real-Time Data Processing Framework for High-Throughput Applications".

[11] P. Dhiman, A. Kaur, Y. Hamid, E. Alabdulkreem, H. Elmannai, and N. Ababneh, "Smart Disease Detection System for Citrus Fruits Using Deep Learning with Edge Computing," Sustainability, vol. 15, no. 5, p. 4576, Mar. 2023, doi: 10.3390/su15054576.

[12] A. Singh et al., "Recent Advancement in Postharvest Loss Mitigation and Quality Management of Fruits and Vegetables Using Machine Learning Frameworks," J. Food Qual., vol. 2022, pp. 1–9, Jun. 2022, doi: 10.1155/2022/6447282.

[13] D. Q. Zeebaree, H. Haron, A. M. Abdulazeez, and S. R. M. Zeebaree, "Combination of K- means clustering with Genetic Algorithm: A review," vol. 12, no. 24, 2017.

[14] D. Q. Zeebaree, H. Haron, A. M. Abdulazeez, and S. R. M. Zeebaree, "Combination of K- means clustering with Genetic Algorithm: A review," vol. 12, no. 24, 2017.

[15] D. Q. Zeebaree, H. Haron, A. M. Abdulazeez, and S. R. M. Zeebaree, "Combination of K- means clustering with Genetic Algorithm: A review," vol. 12, no. 24, 2017.

[16] R. Avdal Saleh and S. R. M. Zeebaree, "Transforming Enterprise Systems with Cloud, AI, and Digital Marketing," Int. J. Math. Stat. Comput. Sci., vol. 3, pp. 324–337, Mar. 2025, doi: 10.59543/ijmscs.v3i.13883.

[17] R. Avdal Saleh and S. R. M. Zeebaree, "Transforming Enterprise Systems with Cloud, AI, and Digital Marketing," Int. J. Math. Stat. Comput. Sci., vol. 3, pp. 324–337, Mar. 2025, doi: 10.59543/ijmscs.v3i.13883.

[18] R. Avdal Saleh and S. R. M. Zeebaree, "Transforming Enterprise Systems with Cloud, AI, and Digital Marketing," Int. J. Math. Stat. Comput. Sci., vol. 3, pp. 324–337, Mar. 2025, doi: 10.59543/ijmscs.v3i.13883.

[19] D. M. Ahmed et al., "A State of Art for Survey of Combined Iris and Fingerprint Recognition Systems," Asian J. Res. Comput. Sci., pp. 18–33, Jun. 2021, doi: 10.9734/ajrcos/2021/v10i130232.

[20] A. Alsirhani, M. H. Siddiqi, A. M. Mostafa, M. Ezz, and A. A. Mahmoud, "A Novel Classification Model of Date Fruit Dataset Using Deep Transfer Learning," Electronics, vol. 12, no. 3, p. 665, Jan. 2023, doi: 10.3390/electronics12030665.

[21] A. U. Alam, P. Rathi, H. Beshai, G. K. Sarabha, and M. J. Deen, "Fruit Quality Monitoring with Smart Packaging," Sensors, vol. 21, no. 4, p. 1509, Feb. 2021, doi: 10.3390/s21041509.

[22] B. Xiao, M. Nguyen, and W. Q. Yan, "Fruit ripeness identification using YOLOv8 model," Multimed. Tools Appl., vol. 83, no. 9, pp. 28039–28056, Aug. 2023, doi: 10.1007/s11042-023-16570-9.

[23] C. C. Ukwuoma, Q. Zhiguang, M. B. Bin Heyat, L. Ali, Z. Almaspoor, and H. N. Monday, "Recent Advancements in Fruit Detection and Classification Using Deep Learning Techniques," Math. Probl. Eng., vol. 2022, pp. 1–29, Jan. 2022, doi: 10.1155/2022/9210947.

[24] D. Gerdan Koç and M. Vatandaş, "Classification of Some Fruits using Image Processing and Machine Learning," Turk. J. Agric. - Food Sci. Technol., vol. 9, no. 12, pp. 2189–2196, Dec. 2021, doi: 10.24925/turjaf.v9i12.2189-2196.4445.

[25] F. V. M. Alvaro, T. G. Aygumov, and M. M. Matygov, "Training of a Convolutional Neural Network for the Classification of Coffee Fruit State," E3S Web Conf., vol. 537, p. 10023, 2024, doi: 10.1051/e3sconf/202453710023.

[26] F. Yuesheng et al., "Circular Fruit and Vegetable Classification Based on Optimized GoogLeNet," IEEE Access, vol. 9, pp. 113599–113611, 2021, doi: 10.1109/access.2021.3105112.

[27] H. Singh Gill, O. Ibrahim Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Fruit Image Classification Using Deep Learning," Comput. Mater. Contin., vol. 71, no. 3, pp. 5135–5150, 2022, doi: 10.32604/cmc.2022.022809.

****