Adaptability of deep learning: datasets and strategies in fruit classification

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Abstract. This review aims to uncover the multifaceted landscape of methodologies employed by researchers for accurate fruit classification. The exploration encompasses an array of techniques and models, each tailored to address the nuanced challenges presented by fruit classification tasks. From convolutional neural networks (CNNs) to recurrent neural networks (RNNs), and transfer learning to ensemble methods, the spectrum of approaches underscores the innovative strategies harnessed to achieve precision in fruit categorization. A significant facet of this review lies in the analysis of the various datasets utilized by researchers for fruit classification. Different datasets present unique challenges and opportunities, thereby shaping the design and effectiveness of the models. From widely recognized datasets like Fruits-360 to specialized collections, the review navigates through a plethora of data sources, elucidating how these datasets contribute to the diversity of research endeavors. This insight not only highlights the variety in fruit types and attributes but also emphasizes the adaptability of deep learning techniques to accommodate these variations. By amalgamating findings from diverse articles, this study offers an enriched understanding of the evolving trends and advancements within the domain of fruit classification using deep learning. The synthesis of methodologies and dataset variations serves to inform future research pursuits, aiding in the refinement of accurate and robust fruit classification methods. As the field progresses, this review stands as a valuable compass, guiding researchers toward impactful contributions that enhance the accuracy and applicability of fruit classification models.

1 Introduction

Fruits, nature's vibrant and diverse gifts, hold a profound significance in our day-to-day lives that transcends their delicious flavors and colorful appearances. These remarkable botanical wonders have been a cornerstone of human nutrition and culture for millennia [1]. As we navigate the hustle and bustle of modern life, it is easy to overlook the immense importance of fruits as a vital source of essential nutrients, natural sweetness, and culinary versatility.

Fruits are rich in essential vitamins and minerals such as vitamin C, potassium, and folate, which are crucial for maintaining our health and well-being [2]. They are also packed with antioxidants, compounds that help protect our bodies from oxidative stress and chronic diseases [3]. Additionally, fruits are an excellent source of dietary fiber, which aids in digestion, regulates blood sugar levels, and promotes a feeling of fullness [4].

To procure a particular type of fruit, the significance of fruit classification becomes abundantly clear. Fruit classification is the systematic categorization of fruits based on various criteria such as botanical characteristics, morphology, and usage. This process allows us to differentiate fruits and group them into categories, facilitating a deeper understanding of their diversity and characteristics [5]. Fruits are commonly classified into types such as simple fruits (developing from a single ovary), aggregate fruits (formed from a single flower with multiple ovaries), and multiple fruits (resulting from the fusion of ovaries from multiple flowers). Each of these types is further subdivided based on specific attributes like whether the fruit is fleshy or dry, dehiscent or indehiscent, and more.

Exploring the classification of fruits, we encounter two main approaches: traditional and automated methods. These distinct approaches provide unique insights into the world of fruit taxonomy and hold varying degrees of relevance in our modern age. Traditional fruit classification is based on botanical and physical traits like size, shape, color, and seeds. It's vital in agriculture, botany, and taxonomy for categorizing fruits and understanding their diversity. In contrast, the modern era has ushered in automated methods for fruit classification, driven by technological advancements, particularly in the fields of machine learning and computer vision [6].

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Automated fruit classification leverages the power of algorithms and artificial intelligence to identify and categorize fruits based on visual data. This approach involves training machine learning models, such as Convolutional Neural Networks (CNNs), on extensive datasets of fruit images.

1.1 Deep learning

Deep Learning (DL), a subset of machine learning, has profoundly transformed various domains, ushering in a paradigm shift in academia, healthcare, finance, and agriculture [7,8]. In education, DL has revolutionized pedagogical strategies through personalized learning platforms, adaptive assessment systems, and intelligent tutoring systems, tailoring education to individual needs [9]. In healthcare, DL's image and speech recognition capabilities have accelerated disease diagnosis, while predictive models have enhanced patient outcomes through early intervention [10–16]. Financial institutions benefit from DL's risk assessment, fraud detection, and algorithmic trading algorithms, enhancing decision-making processes [17]. Moreover, DL has revolutionized agriculture by enabling precision farming through data-driven decision-making, enhancing crop disease detection, predicting yields, and optimizing resource utilization [18–21]. DL-powered weed management and livestock monitoring promote sustainability and animal welfare. Furthermore, DL assists in supply chain management, climate resilience, and market forecasting, ensuring food safety, reducing waste, and maximizing profits.

When it comes to fruit classification, deep learning has turned out very effective, offering numerous advantages in automating and optimizing the sorting and grading processes in agriculture and the food industry. Using Convolutional Neural Networks (CNNs) and other DL architectures, fruit classification systems can accurately distinguish between different fruit types and their various grades based on visual attributes, such as size, color, texture, and shape.

One significant application of DL in fruit classification is in the agricultural sector, where it is utilized for sorting and grading fruits as they are harvested. DL-powered sorting machines can rapidly process large quantities of fruits, classifying them into different categories based on predefined quality criteria. This automation reduces labor costs, improves accuracy, and ensures consistent quality in the final product.

1.2 Objectives

The objective of this critical review is to comprehensively assess the state of the art in fruit classification utilizing deep learning methodologies. This review aims to:

1. Literature Review: Conduct an extensive literature review on deep learning applications in fruit classification to understand the current state of research.
2. Data Extraction and Analysis: Extract relevant data from the Web of Science database and analyze it to identify trends and distribution of research articles and conference papers.
3. Model Performance Assessment: Evaluate the reported model performance metrics, focusing on accuracy, and identify factors influencing model performance, such as dataset size and model choice.
4. Challenges and Limitations Identification: Identify and discuss the challenges and limitations associated with deep learning-based fruit classification, including dataset size disparities and model interpretability.
5. Future Directions Exploration: Investigate emerging trends and future directions in the field, considering areas like multi-modal sensing, interpretable AI, and human-AI collaboration in fruit classification.

2 Material and method

In this critical review, we conducted an exploration of the Web of Science database. We utilized the following search string to extract data from the database:
Search String "Deep Learning" AND "Fruit Classification" NOT "Disease".

Note: all of these keywords were employed to retrieve data from various fields, including the title, abstract, author keywords, and Keywords Plus.

In our quest to retrieve research articles using the aforementioned search string, we identified a total of 52 studies as of September 16, 2023. Within this pool of studies, we discerned the following distribution: 40 research articles and 12 conference papers. Subsequently, we narrowed our focus to research articles that focus only on classification, resulting in a selection of 21 articles for further examination.

In the pursuit of advancing fruit classification using deep learning, researchers have employed diverse methodologies and datasets to develop accurate and efficient models. This section provides an overview of the methodologies commonly utilized in the studies summarized in Table 1 and highlights the characteristics of the datasets employed for training and evaluation.

3 Results

3.1 Model architectures

Deep learning models serve as the backbone of fruit classification systems, and researchers have explored a spectrum of architectures tailored to their specific objectives. These models encompass both established and novel approaches:

- Proposed Models: Hossain et al. [22] introduced a novel architecture in their study, while Altaheri et al. [23] leveraged pre-trained VGG16 and AlexNet models. Similarly, Faisal et al. [26] and Faisal et al. [27] adopted VGG19 and ResNet, respectively, as their base models. Ni et al. [28] explored GoogLeNet, and Shahi et al. [35] employed MobileNetV2.
- Instance Segmentation: Le et al. [25] embraced the Mask R-CNN architecture, particularly suited for tasks requiring instance-level segmentation. This allowed them

to differentiate and classify individual bananas within the same image.

• Ensemble Approaches: In some instances, researchers amalgamated multiple deep learning models to enhance classification performance. For instance, Altaheri et al. [23] combined VGG16 and AlexNet, achieving remarkable accuracy.

• Specialized Architectures: Azadnia et al. [40] proposed a custom architecture for hawthorn fruit classification, while Phan et al. [41] utilized ResNet-101 for tomato classification.

Table 1. Summary of Deep Learning Approaches in Fruit Classification Studies.

Paper	Base Model/ Proposed	Dataset	Public/Private (self-created)	Classes	Number of images	Data augmentation	Transfer Learning	Accuracy
Hossain et al. [22]	Proposed	Date Fruit	Public	4	4000	Yes	Yes	99.2
Altaheri et al. [23]	VGG16, AlexNet	Date Fruit	Private	5	8072	Yes	Yes	99.01, 99.56
Hossain et al. [24]	VGG16	MIX Fruit	Private	10	5946	Yes	Yes	99.75
Le et al. [25]	Mask R-CNN	Banana	Public	2	194	Yes	Yes	96.5
Faisal et al.[26]	VGG19	Date Fruit	Public	7	8,079	Yes	Yes	99.4
Faisal at al. [27]	ResNet	Date Fruit	Public	5	8,079	Yes	Yes	99.10
Ni et al. [28]	GoogLeNet	Banana	Private	6	-	Yes	Yes	98.92
Xue at al. [29]	CAE-AND	MIX fruit	Public	26	124,212	No	Yes	93.78
Chen et al. [30]	Proposed	MIX fruit	Public	30	12,000	No	No	99.03
Gill et al.[31]	Proposed	MIX fruit	-	10	360	No	No	-
Kang et al.[32]	ResNet	MIX Fruit	Public	7	11,632	Yes	Yes	97.43
Ufuah et al. [33]	DenseNet	Date Fruit	Private	3	1,800	Yes	Yes	99.0
Siddiqi [34]	VGG16	MIX Fruit	Private	7	3000	Yes	Yes	94.82
Shahi et al. [35]	MobileNetV2	MIX Fruit	Public	53	15,737	Yes	Yes	96.24
Albarrak et al. [36]	MobileNetV2	Date fruit	Private	8	917	Yes	Yes	99.0
Shankar et al.[37]	DenseNet169	MIX Fruit	Public	15	2633	Yes	Yes	99.84
Mimma et al[38]	RestNet	MIX fruit	Public	30	971	Yes	Yes	99.0
Wang et al.[39]	MobileNetV3	Mix fruit	Public	11	2278	Yes	Yes	95.0
Azadnia et al.[40]	Proposed	Hawthorn	Private	3	600	Yes	Yes	99.63
Phan et al.[41]	ResNet-101	Tomato	Private	3	1508	Yes	No	98
Gulzar [42]	MobileNetV2	Mix fruit	Public	40	26,149	Yes	Yes	99

3.2 Data augmentation

The augmentation of training data plays a pivotal role in enhancing model robustness and generalization [43, 44]. Most studies incorporated data augmentation techniques such as rotation, scaling, flipping, and introducing noise to artificially diversify the training dataset. This augmentation strategy helped mitigate overfitting and enabled models to handle variations in fruit appearance effectively.

3.3 Transfer learning

Transfer learning, a prevalent strategy, involved initializing models with pre-trained weights, often from large-scale image datasets like ImageNet. Researchers fine-tuned these models on their specific fruit classification tasks. Transfer learning expedited convergence and leveraged previously learned features for improved performance.

3.4 Datasets

Public Datasets: Several publicly available fruit datasets served as the foundation for numerous studies. Notable among them is the "Date Fruit" dataset, a standardized benchmark for date fruit classification. Additionally, mixed fruit datasets with varying numbers of classes were employed, offering a comprehensive range of fruit types for training and evaluation.

Private Datasets: In certain cases, researchers collected and curated their private datasets to address specific research objectives or fruit types not adequately represented in public datasets. These private datasets allowed for customization and control over data quality and labeling.

3.5 Dataset characteristics

- Number of Classes: The number of fruit classes in these datasets varied considerably, ranging from 2 to 53 classes. This variability catered to the diverse range of fruit types and research goals.
- Number of Images: Datasets contained varying quantities of images, spanning from a few hundred to over a hundred thousand. The size of the dataset significantly influenced model performance.
- Data Augmentation: Data augmentation techniques were extensively applied in both public and private datasets to enrich the training data.
- Transfer Learning: Transfer learning was a common practice, enabling models to benefit from pre-trained knowledge and adapt it to fruit classification tasks.

3.6 Model performance

Model performance in fruit classification studies is typically measured by accuracy, and the table presents a variety of accuracy scores from different research papers. Here, we will analyze and discuss the model performance trends and highlights:

- High Accuracy Across the Board: One notable trend in the table is the consistently high accuracy achieved by most of the models. Many studies report accuracy scores well above 95%, with several even surpassing the 99% mark. This indicates that deep learning models are highly effective in fruit classification tasks, regardless of the specific architecture or dataset used.
- Influence of Dataset Size: Larger datasets often result in better model performance. For instance, the "MIX Fruit" dataset used by Chen et al. [30] and the "MobileNetV2" dataset by Gulzar [42], both with substantial numbers of images, achieved accuracy scores of 99.03% and 99%, respectively. Similarly, the "Date Fruit" dataset with 8,079 images used by Faisal et al. [27] and Faisal et al. [26] also yielded high accuracy scores of 99.1% and 99.4%.
- Effect of Model Choice: While the choice of deep learning model architecture varies across studies, it is evident that several models, including VGG16, ResNet, and MobileNetV2, consistently perform well. For example, Shahi et al. [35] achieved an accuracy of 96.24% using MobileNetV2, while Shankar et al. [37] obtained an impressive 99.84% accuracy with DenseNet169. This demonstrates the robustness of these architectures in fruit classification tasks.
- Private vs. Public Datasets: The table includes studies that used both public and private datasets. Interestingly, some private datasets, such as those used by Altaheri et al. [23] and Albarrak et al. [36], outperformed public datasets in terms of accuracy, indicating the potential benefits of curated, domain-specific datasets.
- Specialized Architectures: In some cases, specialized architectures tailored for specific fruit types, like the hawthorn fruit in Azadnia et al. [40], performed exceptionally well, achieving an accuracy score of 99.63%. This suggests that custom architectures can be highly effective for niche fruit classification tasks.
- Impact of Data Augmentation and Transfer Learning: Most studies employed data augmentation and transfer learning, which contributed to improved model generalization and accuracy. These techniques allowed models to adapt to variations in fruit appearance and leverage pre-trained knowledge from large-scale datasets.

4 Challenges and limitations

In the realm of fruit classification using deep learning, numerous challenges and limitations shape the landscape. These challenges and limitations are discussed as follows:

- Dataset Size Disparities: One of the primary challenges in fruit classification using deep learning is the variability in dataset sizes. While some studies have access to extensive datasets with tens of thousands of images, others are constrained by smaller datasets. This size disparity can significantly impact model performance, with larger datasets generally resulting in more robust models. Researchers with limited access to data may face challenges in achieving comparable accuracy levels.
- Private Dataset Dependency: Several studies rely on private datasets that are not publicly accessible. While private datasets offer the advantage of customization and domain-specific labeling, they can also limit the reproducibility and comparability of research. The lack of standardized public datasets for specific fruit types may hinder collaboration and benchmarking across studies.
- Class Imbalance: In fruit classification tasks, class imbalance is a common issue, particularly when dealing with datasets containing numerous fruit classes. This can lead to biased models that perform well on majority classes but struggle with minority classes. Addressing class imbalance through techniques like oversampling, undersampling, or generating synthetic data can be challenging and requires careful consideration.
- Computational Resources: Deep learning models, especially those with complex architectures and large datasets, demand substantial computational resources. Training and fine-tuning models can be computationally expensive and time-consuming, limiting the accessibility of this technology to researchers with limited resources.
- Generalization to New Fruit Types: Many studies focus on specific fruit types or a limited number of fruit

varieties. The challenge lies in extending the applicability of models to novel or previously unencountered fruit types. Models trained on one set of fruits may not generalize well to entirely different types, necessitating retraining or adaptation.

• Interpretable Models: Deep learning models, particularly those with intricate architectures, can be challenging to interpret. Understanding why a model makes a specific classification decision is essential, especially in applications where interpretability is crucial, such as quality control in the food industry.

• Model Robustness: While high accuracy rates are impressive, the robustness of models in real-world scenarios with variations in lighting, background, and fruit deformities remains a limitation. Ensuring that models perform well under diverse conditions is an ongoing challenge.

• Scalability: The scalability of fruit classification models for large-scale agricultural or industrial applications is a concern. Deploying these models across vast fruit processing facilities or agricultural fields requires efficient hardware, real-time processing capabilities, and scalability considerations.

5 Applications and implications

Fruit classification using deep learning holds immense promise and is poised to revolutionize several industries and domains. This technology's applications and implications are far-reaching. Some of them are mentioned as follows:

• Agriculture and Quality Control: Fruit classification using deep learning has significant implications in agriculture. Accurate identification of fruit types and quality assessment can aid in automated harvesting, sorting, and quality control processes. This technology can optimize resource allocation and reduce waste in fruit production.

• Food Processing Industry: The accurate classification of fruits can enhance the efficiency of fruit processing facilities. Automated sorting based on quality and ripeness can lead to improved product quality and reduced processing time. This can be particularly valuable in industries such as juice production and canning.

• Consumer Convenience: Deep learning-based fruit classification can extend to consumer applications, including mobile apps and devices that help consumers identify fruits quickly and accurately. This can assist in making informed dietary choices and provide information on fruit ripeness.

• Disease Detection: Beyond classification, deep learning models can be adapted for disease detection in fruit crops. Early detection of diseases or pests can enable timely intervention and reduce crop losses, contributing to sustainable agriculture.

• Research and Biodiversity Conservation: Fruit classification aids researchers in studying fruit varieties, tracking biodiversity, and understanding fruit-bearing plant species. This information can be crucial for ecological and conservation studies.

• Market Demand and Export: Accurate fruit classification can help meet market demands by ensuring that the right types and qualities of fruits are available. It can also facilitate the export of fruits by complying with international standards.

6 Emerging trends and future directions

• Multi-Modal Sensing: Integrating multiple sensing modalities, such as vision and spectroscopy, can enhance fruit classification accuracy. Emerging research is likely to explore the fusion of data from various sensors to improve fruit assessment.

• Edge Computing: Future directions may involve the deployment of lightweight deep learning models on edge devices, allowing real-time fruit classification directly in the field or at processing facilities. This reduces latency and minimizes the need for extensive computational resources.

• Few-Shot Learning: Developing models that can classify fruits with minimal labeled data (few-shot learning) is an emerging trend. This can be particularly valuable for rare or newly discovered fruit types.

• Interpretable AI: As the demand for transparency and accountability in AI systems grows, future research may focus on developing interpretable models that provide explanations for their classification decisions. This is especially relevant in quality control and food safety applications.

• Transfer Learning Across Domains: Transfer learning techniques can be extended to transfer knowledge from one fruit type to another or even across different domains (e.g., from vegetables to fruits). This can reduce the need for large labeled datasets for each fruit type.

• Robustness and Adaptability: Researchers will likely continue to work on enhancing model robustness and adaptability to varying environmental conditions, including changes in lighting, fruit deformities, and background noise.

• Human-AI Collaboration: The future may see the development of collaborative systems where humans and AI work together in fruit classification tasks. AI can assist human experts in faster and more accurate assessments.

7 Conclusion

The landscape of fruit classification using deep learning is marked by a diverse array of models, datasets, and methodologies. The research efforts showcased in section 2 have illuminated both the potential and the challenges of applying deep learning to fruit classification. These studies have underscored the significance of dataset size, with larger datasets often yielding more robust models, but have also highlighted the limitations faced by researchers with constrained access to data.

Furthermore, the reliance on private datasets, while offering customization advantages, has raised concerns about research reproducibility and collaboration. The challenge of class imbalance in fruit datasets has been acknowledged, necessitating the application of specialized techniques to ensure fair and accurate model training.

The demand for computational resources, particularly for complex models and large datasets, has surfaced as a noteworthy limitation, potentially restricting the accessibility of deep learning technology. Generalization to new and previously unencountered fruit types remains a challenge, calling for adaptability and retraining of models.

Additionally, the need for interpretable AI models has become apparent, particularly in contexts such as food quality control. Ensuring model robustness under diverse conditions and scaling these technologies for large-scale applications present ongoing challenges in the field.

Despite these challenges, the studies in section 2 have showcased remarkable achievements, with several models achieving high accuracy rates in fruit classification. As we look to the future, the field is poised for exciting developments, including multi-modal sensing, edge computing, few-shot learning, interpretable AI, transfer learning, and innovative human-AI collaboration models.

These emerging trends and future directions hold the promise of making fruit classification technology more versatile, accessible, and adaptable across various industries and research domains. Overall, the insights gained from the studies in section 2 pave the way for continued advancements in fruit classification using deep learning, with broader applications and far-reaching implications in agriculture, food processing, consumer services, research, and beyond.

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