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VarietyQuest: Data-Driven Exploration of Apple Fruit Variety Classification Frameworks

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Abstract:
The Kashmir valley is known for its breathtaking landscapes and the cultivation of a variety of fruits, with apples being one of the most popular. The Kashmiri apple has a distinct flavor and is widely appreciated for its quality, leading to its export to various destinations around the globe. The sorting and packaging of apples remain a significant challenge due to the lack of skilled labor and the sheer volume of apples produced in the season. As a result, a considerable amount of the harvest is either lost or damaged, leading to significant financial losses. To address this issue, automated classification systems for categorizing fruit varieties using machine learning-based techniques are being developed. Such systems could potentially lead to increased productivity while simultaneously reducing labor costs and errors in sorting and classification. This article provides an overview of the data-driven methodologies for the automated categorization of apple varieties, exploring both conventional and state-of-the-art approaches. The article also provides a concise discussion of the datasets employed in these frameworks. Our study identifies machine learning as a critical foundation for most Apple variety classification frameworks. Further, the absence of datasets for the Kashmiri apple variety is noted during the survey, highlighting the need for further research in this domain. Overall this research explores the automated classification and packaging systems, which can streamline the process and minimize losses while contributing to the growth of the Apple industry across the globe.

Index terms: Apple variety classification framework, automated packaging, computer vision, deep learning, data-driven methodologies

I. INTRODUCTION

Fruits of diverse varieties are ubiquitous, and most of us are familiar with the different kinds that bloom, grow in gardens, or are edible. Across the world, there is an extensive range of fruit species, and the Indian state of Kashmir is particularly renowned for its apples. In several areas of Kashmir, the plant nursery industry has emerged as a vital source of employment, and improved varieties and high-quality seeds are essential for sustainable agriculture that forms the basis for long-term economic growth in developing economies. The region boasts 113 different apple varieties, including delicious, golden, Kulu, and other popular types. Nearly 55% of the state's 1,50,000 hectares of horticulture are dedicated to apple cultivation. Known as the "apple basket," Kashmir is India's top apple-producing state, with an annual economic output exceeding Rs 2500 crores. Kashmir apples are considered the finest apples in India, containing high nutritional fiber, flavonoids, antioxidants, and vitamin C, making them a healthy choice. While most apples are produced in districts such as Srinagar, Ganderbal, Budgam, Baramulla, Kupwara, Anantnag, and Shopian, smaller amounts are also grown in Udhampur, Doda, Poonch, Ramban, and Reasi.

As we move towards an artificial intelligence-driven globe, machines are increasingly replacing human expertise in various fields. Agriculture is one such domain where intelligent devices can simplify work and outperform humans. Advanced artificial intelligence systems are crucial because they have the potential to eliminate ambiguity and increase efficiency. Fruit recognition is a crucial research area in image processing and computer vision. Despite the development of numerous methods, the current computer models for fruit recognition face several challenging problems. One such issue is the accurate extraction and analysis of fruit characteristics for categorization and classification. Most algorithms rely on fruit visual characteristics such as shape and color to recognize their variety. In agriculture, intelligent machines that can simplify work and outperform human professionals are in high demand.

Around 5% to 15% of Apple fruits go to waste because of skilled labor for classifying their varieties. Moreover, human perception subjectivity leads to inaccurate fruit identification and classification. Thus, fruit classification is a critical problem for many industrial applications. For instance, a fruit classification system can assist supermarket cashiers in distinguishing between various fruit species and their prices. Moreover, it can help determine whether a specific fruit type meets someone's dietary requirements. To address these challenges, the fruit sector needs an automated system. The potential of Deep learning approaches to provide intelligence for creating an automated system that distinguishes fruits based on their type, variety, maturity, and intactness is enormous. In unpredictable fields like agriculture, deep learning-based models have become state-of-the-art approaches for image segmentation and classification.

Although a lot of surveys have been conducted on fruit variety classifications, to the best of our knowledge, no previous research surveys have been specifically done to comprehensively summarize the frameworks of apple fruit varieties, making our study unique in this regard. Inspired by this research gap, we decided to review the literature on the apple fruit variety classification frameworks. We comprehensively review the methodologies, benchmark datasets, open research challenges, and future scopes of the fruit variety classification frameworks. The following are the significant contributions of our research.

a. To conduct an in-depth investigation of apple fruit variety classification frameworks using our proposed taxonomy.
b. To perform a parametric comparison of the benchmark dataset used for training and testing.
c. To identify and highlight open research challenges and future opportunities in the field of fruit variety classification.

The rest of the article is structured as follows: Section II presents the general architecture and taxonomy of the apple fruit classification systems. Section III provides a thorough review of the frameworks employed in fruit variety classification. Section IV examines the benchmark datasets used in fruit variety classification frameworks for training and testing. Lastly, in sections V and VI, open research issues and conclusions are discussed, respectively.

II. APPLE FRUIT VARIETY CLASSIFICATION FRAMEWORK

An apple variety classification framework (AVCF) that comprises a sequence of feature extractors, a feature analyzer, and a discriminator, is illustrated in Figure 1.

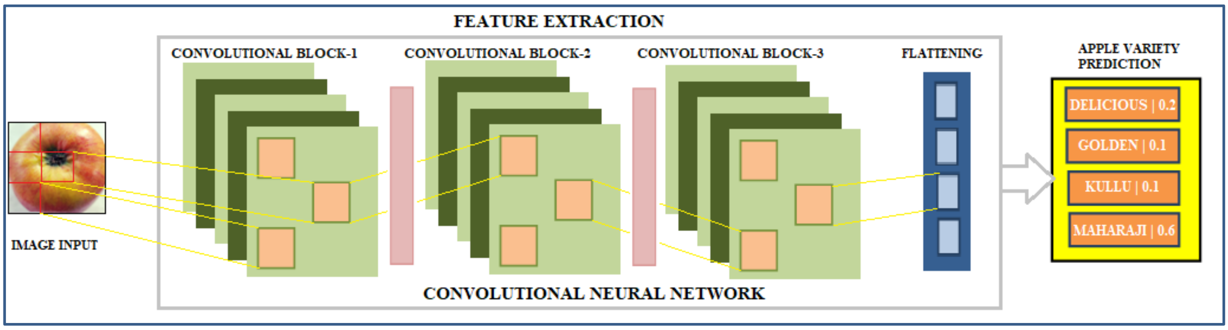

Figure 1: A generic deep learning-based architecture of Apple Variety Classification framework

The feature extractor is responsible for extracting features from input images and transmitting them to the feature analyzer. The feature analyzer refines the input features to make them suitable for the discriminator's decision-making process. The final determination of the apple variety for the input images is made by the discriminator. Initially, handcrafted feature extraction based on machine learning was employed. However, due to the growing interest in deep learning models, such as Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), implicit feature extraction is now performed. Similarly, traditional machine learning-based models like Support Vector Machines (SVM), Linear Regression, and other techniques were used in the past to decide on the variety, but now, deep learning-based approaches are predominantly used. It should be noted that large datasets are required to train deep learning models to achieve an acceptable level of performance. We devised a new taxonomy for AVCF, depicted in Figure 2, based on the type of architecture and feature extraction and discrimination techniques employed.

At an abstract level, these frameworks can be categorized into two fundamental classes based on whether they utilize machine learning-based handcrafted features or implicit feature extraction techniques. There are additional categories within machine learning and deep learning-based frameworks, which can be classified according to the models they employ. A brief overview of these models is presented below.

a. KNN-based AVCF: One of the simplest machine learning algorithms, based on the supervised learning method, is K-Nearest Neighbor. The KNN method assumes that the new sample and the existing samples are comparable, and it places the new sample instance in the category that is most like the existing categories.
b. Support vector machine-based AVCF: One of the most well-liked algorithms for supervised learning is called the Support Vector Machine (SVM), and it is used to solve both classification and regression issues. The SVM algorithm's objective is to establish the optimal decision boundary or line that can divide n-dimensional space into output classes.
c. Decision tree-based AVCF: A decision tree is a method for figuring out potential actions and their effects (often in terms of cost). Decisions and their effects are displayed as lines connecting.
d. Random forest-based AVCF: A random forest-based framework is a technique for classification, regression, and other ensemble learning tasks that builds a large number of decision trees during

training. The class that the majority of the trees choose as their output in a classification exercise is known as the random forest.

e. Clustering-based AVCF: Clustering is the process of grouping the population or data points so that they are distinct from the data points in other groups and more comparable to one another. It is a grouping of things based on how similar and distinct they are to one another.

Deep learning-based frameworks utilize ANNs or CNNs to extract and aggregate features, employing implicit feature extraction methods directly. The input data undergoes a sequence of convolutional and pooling layers, with the resulting feature maps flattened to make a final determination of the apple variety.

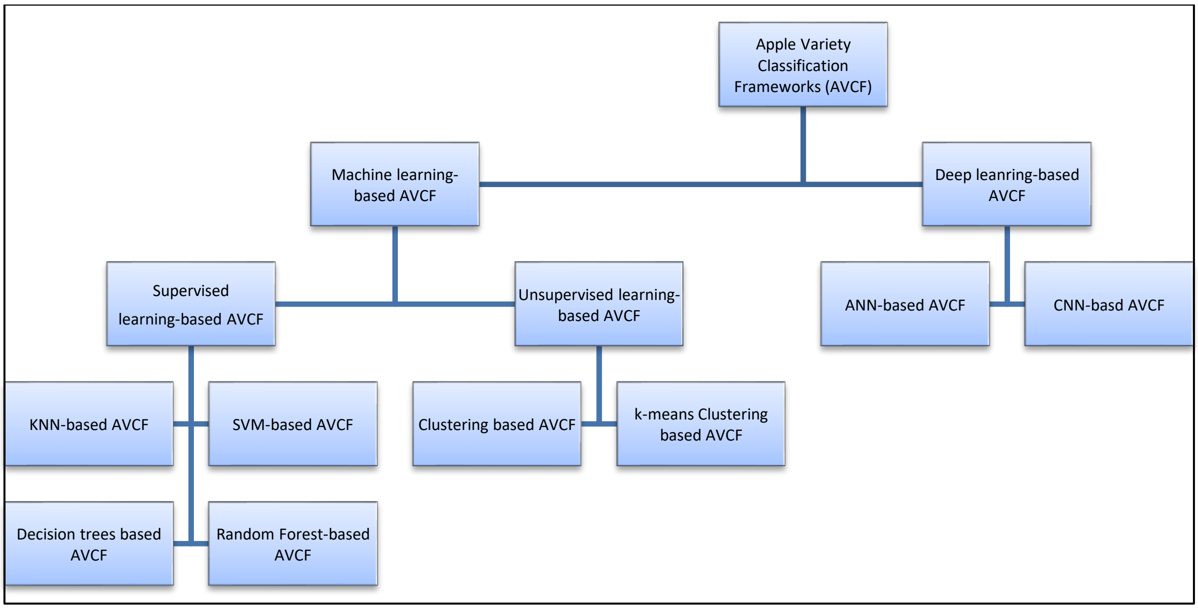

Figure 2: A comprehensive taxonomy of apple fruit variety classification frameworks

III. REVIEW OF LITERATURE

Kadir et al. [1] proposed that shape, vein, color, and texture should be taken into consideration at once. A neural network known as the Probabilistic Neural Network (PNN) is employed as a classifier. The Flavia dataset taken for the experiment, which contains 32 different types of plant leaves, the classification method produced an average accuracy of 93.75%, according to the experimental results. Kumar et al. [2] present an efficient plant leaf recognition system that makes use of morphological features and adaptive boosting techniques. Three alternative classification techniques namely KNN, decision tree, and multilayer perceptron are used to execute the experimental outcomes with an accuracy of 89.42%. Li et al. [3] utilized a shallow CNN classifier for apple classification. Collection and labeling of several apple image shave been done primarily by them. Training data is then obtained through a series of data augmentation methods, the Caffee framework is used to do training and parameter optimization. About classifying images of apples, 92% accuracy is achieved. Bhargava & Bansal [4] developed a novel method to evaluate and classify the fruit quality of various apple species. The six different apple varieties Fuji, York, Golden Delicious, Red Delicious, Granny Smith, and Jonagold —are employed for image collection. By using KNN, linear regression, and SVM classifiers, fresh and rotting apples are classified. The suggested method achieves an accuracy of 92.90% (k= 5), 98.42% (k= 10), and 95.27% (k= 15).

Tripathi & Maktedar [5] primary goal was to examine how well the Naive Bayes algorithm classified different apple fruit kinds and how applicable it is to the task. The methodology involved image acquisition, pre-processing and segmentation, analysis, and classification of apple varieties. Results showed the accuracy estimated, sensitivity, precision, and specificity were 91%,77%,100%, and 80% respectively. Chen et al. [6] develop a deep-learning variety-classification model MAFNet based on the convolution neural network. The model achieves the efficient recognition of 30 varieties of apples planted primarily in Northwest China under complex natural environments and has a more significant advantage in both the accuracy and the number of participants, which enlarges the pool of currently available methods for apple-variety recognition. The model's test set average accuracy is 93.14% at the end. Arlimatti et al. [7] developed an automated classification method for apple fruits. Then, for fruit classification, these characteristics are supplied to the nearest neighbor (NN) supervised classifier, which is easy but effective in some applications. When using the nearest neighbor (NN) classifier, the classification achieves about 92% accuracy. Shawwa & Naser [8] presented a deep learning-based convolutional neural network for apple classification. This model uses a network with four layers and a dropout of 0.2 to predict the type of (previously unobserved) apple photos, taking as input apple images from 13 different varieties. This model uses raw images as input, so they used convolutional neural networks (CNNs) to extract features.

Hossain et al. [9] prepare a deep learning-based fruit classification framework. The system is based on two distinct deep-learning architectures. The first is a six-layer suggested light convolutional neural network model, while the second is a pre-trained deep learning model of fine-tuned visual geometry group 16. The proposed system uses two color picture datasets, one of which is publicly available. On dataset 1, the first and second models each had classification accuracy results of 99.49% and 99.75%. The accuracy of the first and second models on dataset 2 was 85.43% and 96.75%, respectively. Tripathi & Maktedar [10] provides an overview of current machine learning-based methods for identifying and categorizing illnesses in agricultural goods, such as different plants, fruits, and vegetables. The majority of the strategies are based on image processing, while some are based on data mining approaches. This study examines the number of systems based on several factors, such as the product and its disease, that are taken into account, including dataset, methodology, and accuracy findings, including gap analysis. The system employs two classifiers: SVM with a polynomial kernel and SVM with a radial basis kernel. Radial basis kernel SVM accuracy is up to 96%, while polynomial basis kernel SVM accuracy is up to 95%.

Ponce et al. [11] initialized a method for classifying olive fruit varieties, and it is approached as an image classification issue. 2,800 fruits from seven different olive kinds were shot for this purpose. This is done in order to calculate the classifiers that will be used to categorise the different types of fruits. When employing the Inception-ResnetV2 architecture, accuracy is 95.91%. Maludi et al.[12] in their research developed the Manalagi apple fruit classification system by extracting the average RGB colour feature using the backpropagation method. The created system's goal is to discriminate between Manalagi apple fruit that is worth eating and fruit that is not. Based on the fruit's skin's typical RGB colour composition, fruits are categorized. The model yields an 90% accuracy. Altaheri et al. [13] suggests a unique method for classifying and selecting features in date fruit genetic variability using DL architecture. Date fruit images are used as the input in this procedure, which also includes noise reduction, normalisation, and smoothing. Experimental analysis has been performed on a number of date fruit datasets in terms of accuracy, precision, recall, F-1 score, RMSE, and mean precision. The proposed method achieved 97% accuracy, 93% precision, 83% recall, 89% F-1 score, 63% RMSE, and 83% mean precision.

Kausar et al. [14] use a Pure Convolutional Neural Network (PCNN) with the fewest possible parameters in order to more reliably distinguish between different fruits. On the freshly released fruit-360 dataset, they use PCNN to show off classification results. The 55244 colour fruit photos from the 81 categories used in the experiment yielded findings showing that the PCNN achieves a classification accuracy of 98.88%. Nirale et al. [15] developed an adaptive naive bayes (aNB), multiple support vector machines (MSVM), varied depth random forests (VDRF), and interpolated k Nearest Neighbour (ikNN) approaches based frameworks in their work to offer a unique ensemble learning-based framework. These techniques express input fruit images into many domains by using colour, texture, shape, and convolution characteristics. Due to this, the model is capable of obtaining an accuracy of 97.9% for fruit categorization. Raut et al. [16] in their work largely focused on achieving a high accuracy classification for various fruits. Convolution and pooling layers are utilised as necessary and the CNN model provides accuracy of 98.6% after accurate feature extraction and image segmentation analysis.

Sucipto et al. [17] divided apples into categories according to kind, including Braeburn, Granny Smith, Pink Lady, Red Yellow, Golden, and Red Delicious. This study employed 400 testing photos and 500 training images of apples. Linear Discriminant Analysis (LDA) is used as the classification algorithm. 98% accuracy is achieved by their model. Font et al. [20] describes the initial research towards an automated method for classifying nectarine varieties based on colour. This approach is based on the computation of the histogram of the skin colour description in terms of hue, saturation, and value (HSV) of the examined nectarines. These first findings demonstrate the difficulty of the categorization issue caused by the similarity in skin tones between varieties and the resulting quality production issue since various types may have varied tastes and/or flesh colours. Font et al. [18] suggests a convolutional neural network-based solution for fruit automated detection and categorization. They achieved the maximum average classification accuracy of 99.8% on the public data set.

Seng et al. [19] use nearest neighbour classification to classify and identify fruit images based on collected feature values. The suggested fruit recognition system analysis effectively classifies and distinguishes fruits with an accuracy of up to 90%. Table 1 illustrates the comparative and quantitative analysis of various apple categorization frameworks studied during this survey study.

Table 1: A comparative survey of various fruit variety classification frameworks

Year	**Author**	**Technique**	**Classifier**	**Data set**	**Accuracy (%)**
2009	Seng et al. [19]	Machime learning	Nearest Neighbour	Private Dataset	90%
2011	Kadir et al. [1]	Machine Learning	Artificial Neural Network	Flavia Dataset	93.75%
2012	Arlimattiet et al. [7]	Machine Learning	KNN classifier	Private dataset	92%
2012	Font et al. [18]	Machine Learning	HSV	Private dataset	70%
2016	Tripathi & Maktedar [5]	Machine Learning	SVM with radial and polynomial kernel	Private dataset	76%

2018	Hossain et al. [9]	Deep Learning	CNN & VGG 16	Public and own dataset	85.43%
2018	Kausar et al. [14]	Deep Learning	PCNN	Fruit 360	98%
2019	Kumar et al. [2]	Machine Learning	KNN, Decision tree, and Multi-perceptron	Flavia Dataset	89.42%
2019	Shawwa & Naser [8]	Deep Learning	CNN	Fruit 360	90%
2019	Ponce et al. [11]	Deep Learning	Image processing and CNN	Own Dataset	95%
2020	Muladi et al. [12]	Deep Learning	Back propagation	Public dataset	90%
2020	Chen et al. [6]	Deep Learning	CNN	Public and own dataset	90%
2020	Li et al. [3]	Deep Learning	Shallow CNN	Private Dataset	92%
2021	Bhargava & Bansal [4]	Machine Learning	SVM	Private dataset	91%
2021	Sucipota et al. [17]	Machine Learning	LDA	Public Dataset	98%
2022	Raut et al. [16]	Deep Learning	CNN	Private dataset	98%
2022	Nirale et al. [15]	Machine Learning	Navie bayes, Multiple Support Vector Machine , Random Forest ,KNN	Private Dataset	93%

IV. BENCHMARK DATASETS

Machine learning and deep learning-based models require a large amount of data to identify patterns and extract significant features to classify input features accurately. These models are often referred to as data-driven approaches. The effectiveness of an artificial model is directly dependent on the quality of the dataset it is trained on. An optimal dataset must include a sufficient number of representative training samples to enable the model to distinguish between multiple classes accurately. The AVCF uses the following benchmark datasets for training and evaluation purposes.

a. Fruit 360: The Fruit 360 dataset is a popular and comprehensive dataset widely used for fruit recognition tasks. It contains 131 different types of fruits and vegetables with a total of 90483 images. The images were captured under varying lighting conditions and from different angles, making the dataset challenging and realistic. Each image in the dataset is labeled with the fruit type, and the dataset is split into training and testing sets for evaluation purposes. The Fruit 360 dataset has been used extensively in research studies related to fruit recognition, and its availability has facilitated the development and testing of new fruit recognition algorithms. Each of the image samples is of the size 100*100 pixels in jpeg file format.

b. Flavia: The Flavia dataset is a publicly available dataset that consists of leaf images from four different classes of plants, including the families of Oleaceae, Asteraceae, Rosaceae, and Ericaceae. The dataset contains a total of 1907 images captured under controlled conditions and in high-resolution. Each leaf image is represented by a set of 64 shape and texture features, such as contrast, entropy, and energy, which are extracted using image processing techniques. The Flavia dataset is widely used in pattern recognition and computer vision research, particularly for developing and evaluating algorithms for plant classification and identification. It has been shown to achieve high classification accuracy, making it a valuable resource for plant biologists, ecologists, and agronomists.
c. Citrus: The Citrus dataset is a publicly available dataset used for citrus fruit recognition tasks. It contains images of 10 different citrus fruit classes, including lemon, lime, orange, and grapefruit. The dataset comprises a total of 1536 high-resolution images captured under controlled lighting conditions and varying orientations. Each image in the dataset is labeled with the corresponding fruit type, and the dataset is split into training and testing sets for evaluation purposes. The Citrus dataset has been widely used in research studies related to fruit recognition, and its availability has facilitated the development and testing of new fruit recognition algorithms. With its focus on citrus fruits, the dataset has potential applications in the agriculture industry, particularly in the automated sorting and grading of citrus fruits.

V. OPEN RESEARCH CHALLENGES

The following are the open reserach challenges that were observed during the literature review.

a. Incorporating Domain Knowledge: One of the challenges in deep learning-based apple variety classification frameworks is incorporating prior domain knowledge. While deep learning models excel at learning features from data, they may not always capture important domain-specific features. Incorporating such knowledge could improve the accuracy of these models.
b. Dealing with Class Imbalance: In real-world scenarios, the distribution of different apple varieties may not be equal, leading to class imbalance. This can negatively impact the performance of deep learning models, as they tend to be biased towards the majority class. Developing effective techniques to address class imbalance is, therefore, a significant research challenge.
c. Adapting to Varying Environmental Conditions: The performance of deep learning-based apple variety classification frameworks can vary depending on the environmental conditions in which the images are captured. For example, changes in lighting, background, or camera position can affect the accuracy of the models. Developing techniques that can adapt to such variations is an open research challenge.
d. Enhancing Robustness to Adversarial Attacks: Deep learning models are vulnerable to adversarial attacks, where small, imperceptible changes to an input image can cause the model to misclassify it. Developing robust deep-learning models that can withstand such attacks is an ongoing research challenge.
e. Multi-task Learning: Apple variety classification may involve multiple related tasks, such as fruit detection, segmentation, and recognition. Multi-task learning techniques that can learn these tasks simultaneously could be a promising approach for improving the overall performance of deep learning-based Apple variety classification frameworks. Developing such techniques is, therefore, an open research challenge.

VI. CONCLUSIONs

This article provides a systematic review of the frameworks used to classify apple varieties, as well as the current advancements in datasets utilized for this purpose. It is observed that while the primary frameworks for Apple variety classification are based on traditional machine learning-based methods, a few novel approaches have emerged that leverage data-driven deep learning methods, such as object detection models like CNNs. In light of this, future research can focus on developing deep learning-based classification architectures with larger training datasets to enhance their reliability and applicability in real-world scenarios. Moreover, there is a crucial need for creating and integrating fresh samples into existing datasets, as well as exploring more modern deep learning techniques such as vision transformers, pre-training, and transfer learning, to develop more effective apple variety classification frameworks. Therefore, the fruit variety classification domain is likely to remain a prominent area of research in the years to come.

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