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Quality Evaluation of Pomegranate Fruits Using Machine Learning: A Review of Current Trends and Research Gaps

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Abstract:

Quality grading plays a crucial role in determining the market value, consumer acceptance, and export potential of pomegranate fruits. Conventional grading practices, which rely heavily on manual inspection, are often slow, subjective, and inconsistent. With the growing demand for uniform and high-quality produce, especially in international markets, there is an increasing need for automated and reliable grading solutions. Recent advances in machine learning, deep learning, and computer vision have opened new possibilities for non-destructive and accurate fruit quality assessment. This review presents a detailed overview of machine learning-based approaches used for pomegranate quality grading. It discusses image acquisition methods, preprocessing techniques, feature extraction strategies, traditional and deep learning models, evaluation metrics, and practical challenges. In addition, current research gaps and future directions are highlighted to support the development of scalable and industry-ready grading systems. This article aims to serve as a useful reference for researchers and practitioners working in intelligent agriculture and automated fruit grading.

Keywords: Pomegranate, Quality Grading, Machine Learning, Deep Learning, Image Processing, Computer Vision

Introduction:

Science has long been regarded as an Pomegranate (*Punica granatum*) is widely recognized for its nutritional value, medicinal properties, and economic importance. Over the past decade, global demand for high-quality pomegranates has increased significantly, particularly in export-oriented markets where strict quality standards are enforced. As a result, accurate and consistent quality grading has become a critical requirement in post-harvest handling and supply chains.

Traditionally, pomegranate grading is carried out through visual inspection by trained personnel who assess attributes such as color, weight, size, shape and surface defects. While this approach is simple, it suffers from several drawbacks. Human judgment varies with experience, fatigue, and environmental conditions, leading to inconsistent grading results. Moreover, manual grading is time-consuming and unsuitable for large-scale operations, often resulting in economic losses and rejection of export consignments.

To overcome these limitations, researchers have increasingly turned toward machine learning and computer vision techniques. These technologies enable automated, non-destructive assessment of fruit quality by analyzing images and identifying patterns that are difficult to capture through manual inspection. This review examines how such approaches have been applied to pomegranate quality grading and evaluates their effectiveness.

Quality Attributes of Pomegranate Fruit:

The external appearance of pomegranate fruits largely determines their market acceptance. Automated grading systems mainly focus on the following attributes:

1. Color: Color is closely associated with ripeness and freshness. Fruits with uniform and deep red coloration are generally preferred, while uneven coloring or discoloration often indicates inferior quality.

2. Size and Shape: Larger fruits with regular shape are typically graded higher. Irregular or misshapen fruits are usually classified into lower grades despite being internally sound.

3. Surface Texture: Surface texture provides important clues about fruit condition. Roughness, cracks, or scars on the rind can significantly reduce commercial value.

4. Defects: Defects such as sunburn, fungal spots, bruises, and mechanical damage negatively affect shelf life and export quality. Accurate detection of these defects is therefore essential.

Image Acquisition Techniques:

Image acquisition forms the backbone of automated grading systems. Most studies rely on RGB cameras combined with controlled lighting to capture high-quality images.

1. Controlled Imaging Environment:

To minimize variability, researchers often use Uniform LED lighting, Fixed camera positions, Dark or contrasting backgrounds, Multi-angle imaging setups. Such arrangements help ensure consistency and improve feature extraction accuracy.

2. Practical Challenges:

Despite controlled setups, challenges such as reflections from glossy fruit surfaces, variations in fruit orientation, and partial occlusion remain common. Advanced systems address these issues using enclosed chambers and fruit rotation mechanisms.

Image Preprocessing Techniques:

Preprocessing improves image quality and prepares data for analysis. Common steps include: Noise reduction using filters, Image resizing and normalization, Background removal and segmentation, Conversion to alternative color spaces such as HSV or Lab. Accurate segmentation is especially important, as errors at this stage can affect the entire grading process.

Feature Extraction Methods:

Feature extraction converts visual information into numerical values that can be processed by machine learning algorithms.

1. Color Features: Color histograms and statistical measures of color channels are widely used to capture pigmentation characteristics.

2. Shape and Size Features: Geometric features such as area, perimeter, diameter, and circularity help quantify fruit size and shape consistency.

3. Texture Features: Texture analysis methods like GLCM, LBP, and wavelet transforms are effective in detecting surface roughness and subtle defects.

4. Defect-Related Features: Edge detection and contour-based methods are commonly used to identify and measure defect regions.

Traditional Machine Learning Approaches:

Early automated grading systems often relied on handcrafted features combined with classical classifiers.

1. Support Vector Machines (SVM): SVMs are widely used due to their robustness and ability to handle high-dimensional data, especially with limited datasets.

2. K-Nearest Neighbors (KNN): KNN is easy to implement and interpret but becomes computationally expensive for large datasets.

3. Random Forest: Random Forest models handle non-linear relationships well and are relatively resistant to overfitting, making them suitable for feature-based grading.

Although effective, these methods depend heavily on the quality of extracted features.

Deep Learning-Based Methods:

Deep learning has significantly improved performance in image-based grading tasks.

1. Convolutional Neural Networks (CNNs): CNNs automatically learn spatial and hierarchical features directly from images, eliminating the need for manual feature engineering.

2. Transfer Learning: To address limited data availability, many studies use pre-trained models such as VGG, ResNet, MobileNet, and EfficientNet, fine-tuned for pomegranate grading.

Hybrid Models:

Hybrid approaches combine deep learning features with handcrafted features and traditional classifiers.

These models often achieve better accuracy and stability by leveraging the strengths of both approaches, making them more suitable for real-world deployment.

Evaluation Metrics:

Performance of grading systems is commonly measured using Accuracy, Precision and recall, F1-score, Confusion matrix. Cross-validation techniques are frequently employed to ensure reliability and generalization.

Literature Review:

In 2024, Rajinder Kumar M. Math et al. [1] have proposed a CNN-based deep learning technique for real-time pomegranate grading, achieving 99.20% accuracy and 1 for precision, recall, and F-score, using fine-tuning of DenseNet-169 model on a custom dataset with 12 grade-quality classes.

In 2024, Nhan H. Nguyen, et al.[2] have introduces Granny, a machine-learning and image-processing tool designed to enhance the quality assessment of pome fruits, addressing biases and inconsistencies in traditional visual evaluations. By providing objective and high-resolution ratings, Granny ensures compatibility with established standards while improving analyses of starch content, peel defects, and color. Its integration with broader fruit quality metrics and environmental data strengthens research insights. As an open-source solution, Granny offers a valuable resource for advancing post-harvest fruit assessment with greater accuracy and consistency.

In 2024, V. Gopi Kiran et al. [3] have explores the use of digital image processing and machine intelligence to enhance pomegranate sorting, addressing the inefficiencies of manual methods. By leveraging spatial domain, frequency domain, and Histogram of Oriented Gradients (HOG) features, the research trains machine learning classifiers for quality evaluation. The findings highlight that HOG features yield the best results, with an impressive 93.51% accuracy when used with an Artificial Neural Network (ANN). This approach demonstrates a promising advancement in automating fruit sorting, improving both efficiency and precision.

In 2024, Ashoka Kumar Ratha et al.[4] presents a novel approach to pomegranate disease detection and quality assessment using the PF-CNN model, which integrates median filtering and mean/max pooling with transfer learning from ResNet101. By segmenting fruit images and applying advanced feature extraction techniques, the model achieves an impressive 96.21% classification accuracy across five categories. The use of an SVM classifier further enhances precision, enabling timely disease identification and improved management strategies. This research offers a significant advancement in safeguarding pomegranate yield and quality through automated, high-accuracy disease detection.

In 2024, Ahatsham Hayat et al. [5] introduces FruitVision, a deep learning-based model for automatic fruit grading, addressing the limitations of traditional manual assessment. By leveraging computer vision, FruitVision achieves exceptional accuracy, outperforming existing models with scores exceeding 97% across multiple fruit types. The use of 5-fold cross-validation further validates its robustness. This research marks a significant advancement in AI-driven agricultural quality assessment, offering a highly efficient and precise solution for the industry.

In 2024, Abolfazl Hemmati et al. [6] explores the feasibility of using visible near-infrared (Vis-NIR) spectroscopy as a fast, cost-effective, and reliable method for assessing the quality of Persian export pomegranates. By combining the Savitzky–Golay smoothing and standard normal variation normalization models with partial least square regression (PLSR), the approach achieves excellent predictive accuracy, with correlation coefficients above 0.95 for key quality traits. The results demonstrate that Vis-NIR spectroscopy is a promising non-destructive technique for grading pomegranates before export, enhancing marketability and quality control.

In 2023, Rupali Santosh Kale and Sanjay Shitole [7] presents a hybrid CNN-LSTM model with the novel MAdam optimizer for automatic grading and quality classification of pomegranates. By incorporating image augmentation techniques, the model enhances robustness and improves classification accuracy. The use of MAdam optimizes training efficiency by minimizing variance in the adaptive learning rate. Achieving an impressive 99.24% accuracy, the proposed system outperforms comparative models, offering a highly precise and efficient AI-driven solution for fruit grading and quality assessment.

In 2022, Avraam Koufatzis el at.[8] evaluates 14 deep learning models for pomegranate quality assessment, using a novel dataset with three quality classes. The results highlight the effectiveness of transfer learning in fruit sorting tasks, even with limited data. Among the models tested, MobileNet achieved the highest classification accuracy at 94.12%. The findings demonstrate the potential of deep learning for efficient and reliable postharvest fruit grading, aiding in optimal usage and pricing decisions.

In 2022, V. B. Utpat el at.[9] highlights the importance of quality grading in India's pomegranate export industry and explores an automated grading system using machine vision. Traditional manual grading is time-consuming and less efficient, whereas an AI-driven approach ensures faster, error-free classification based on fruit appearance. The paper discusses key processes such as image acquisition, preprocessing, segmentation, and feature extraction, leveraging Artificial Neural Networks (ANN) for quality assessment. This research underscores the potential of automation in enhancing the efficiency and accuracy of pomegranate grading for export.

In 2022, ManishaVikas Bhanuse, and Shanti Patil [10] presents an efficient, non-destructive fruit grading technique using partial least squares-discriminant analysis (PLS-DA) based on texture features. By extracting patterns such as LBP, LDP, LOOP, LGP, and LTP from multispectral images, the method classifies fruits like apples, bananas, pomegranates, and mangoes. It further evaluates key quality parameters, including firmness, soluble solids concentration (SSC), and titratable acidity (TAC). The proposed model achieves a high classification accuracy of 95.67%, demonstrating its effectiveness in enhancing automated fruit grading with precision and reliability.

Table 1: Literature Review

Year	Authors	Methodology	Result/Outcome
2024	Rajinder Kumar M. Math et al. [1]	CNN-based deep learning using DenseNet-169 fine-tuning on a custom dataset with 12 quality grades.	Achieved 99.20% accuracy, with precision, recall, and F-score of 1.
2024	Nhan H. Nguyen et al. [2]	Granny, a machine-learning and image-processing tool for fruit quality assessment.	Ensures objective and high-resolution grading with compatibility to existing standards.
2024	V. Gopi Kiran et al. [3]	Digital image processing and machine intelligence using spatial, frequency, and HOG features for classification.	HOG features with an ANN model yielded 93.51% accuracy.
2024	Ashoka Kumar Ratha et al. [4]	PF-CNN model integrating median filtering and mean/max pooling with ResNet101 and SVM.	Achieved 96.21% classification accuracy across five disease and quality categories.
2024	Ahatsham Hayat et al. [5]	FruitVision, a deep learning-based automatic fruit grading system using computer vision.	Outperformed existing models with over 97% accuracy across multiple fruit types.
2024	Abolfazl Hemmati et al. [6]	Vis-NIR spectroscopy with PLSR model for non-destructive pomegranate quality assessment.	Achieved correlation coefficients above 0.95 for key quality traits.
2023	Rupali Santosh Kale, Sanjay Shitole [7]	Hybrid CNN-LSTM model with MAdam optimizer and image augmentation.	Achieved 99.24% accuracy, improving grading efficiency.
2022	Avraam Koufatzis et al. [8]	Evaluation of 14 deep learning models using transfer learning for pomegranate grading.	MobileNet achieved the highest accuracy at 94.12%.
2022	V. B. Utpat et al. [9]	AI-driven automated grading using machine vision and ANN.	Enhanced grading efficiency for India's pomegranate exports.
2022	Manisha Vikas Bhanuse, Shanti Patil [10]	PLS-DA technique using texture features (LBP, LDP, LOOP, LGP, LTP) for fruit classification.	Achieved 95.67% accuracy in grading apples, bananas, pomegranates, and mangoes.

Challenges and Research Gaps:

Although substantial progress has been made, several limitations persist across existing studies. Most research relies on proprietary or small-scale datasets, limiting reproducibility and cross-study comparison. Real-time implementation and integration with mechanical sorting systems remain underexplored, and few studies address model interpretability or adaptability under varying environmental conditions. These gaps indicate the need for robust, scalable, and deployment-ready machine learning frameworks tailored specifically for pomegranate quality grading.

Future Research Directions:

Looking ahead, research in pomegranate quality grading can be strengthened by building large, carefully annotated datasets that reflect real-world variability in fruit appearance and condition. There is also a clear need to move beyond laboratory experiments and focus on developing grading systems that operate in real time and can be seamlessly integrated with sorting and packaging hardware. To improve user confidence and practical adoption, future studies should explore explainable AI techniques that make model decisions easier to understand and interpret. In addition, combining external visual characteristics with internal quality indicators would allow a more complete and reliable evaluation of fruit quality. Finally, the use of lightweight models optimized for edge devices can enable cost-effective, energy-efficient deployment in farms and packing facilities, making intelligent grading systems more accessible and scalable.

Conclusion:

Machine learning-based approaches have shown strong potential in automating pomegranate quality grading. Deep learning models, particularly CNNs and hybrid frameworks, consistently outperform traditional methods in terms of accuracy and robustness. However, challenges related to scalability, interpretability, and real-world deployment remain. Continued research in this area can lead to reliable, cost-effective, and industry-ready grading solutions that support sustainable and intelligent agricultural practices.

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