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Automated Tomato Quality Classification Using Transfer Learning And Machine Learning Techniques

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ABSTRACT

The increasing demand for high-quality tomatoes that satisfy consumer and market requirements, together with large-scale agricultural production, has highlighted the need for automated inline quality grading systems. Traditional manual grading methods are labor-intensive, time-consuming, and costly, making them unsuitable for large-scale operations. This study proposes a hybrid approach for tomato quality sorting and grading by combining pre-trained convolutional neural networks (CNNs) for feature extraction with conventional machine learning algorithms for classification. A tomato image dataset was created using an NVIDIA Jetson TX1 single-board computer, followed by image preprocessing and fine-tuning techniques to enable deep networks to capture complex and discriminative features. The extracted features were then classified using traditional machine learning classifiers, including Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). Experimental results show that the proposed CNN–SVM hybrid model outperforms other approaches, achieving an accuracy of 96.2% for binary classification (healthy vs. rejected) and 95.4% for multiclass classification (ripe, unripe, or rejected) when InceptionV3 is used as the feature extractor. Furthermore, evaluation on a public dataset demonstrated that the CNN–SVM model achieved an accuracy of 96.8% in classifying tomatoes into ripe, unripe, old, and damaged categories, surpassing other hybrid models. The performance of the proposed system was comprehensively assessed using metrics such as accuracy, precision, recall, specificity, and F1-score, confirming its effectiveness for automated tomato quality grading.

Keywords: Tomato Quality Classification, Transfer Learning, Machine Learning, Image Processing, Deep Learning, Computer Vision, Convolutional Neural Networks (CNN), Agricultural Automation, Fruit Quality Assessment, Smart Agriculture, Feature Extraction, Image-Based Classification.

I. INTRODUCTION

Agriculture plays a fundamental role in sustaining the global population and contributing significantly to national economies. In countries like India, where a large portion of the population depends on farming for livelihood, improving agricultural productivity and product quality is of utmost importance. Among various horticultural crops, tomatoes are one of the most widely cultivated and consumed vegetables worldwide. They are valued for their rich nutritional content, including vitamins A and C, antioxidants such as lycopene, and their extensive use in food processing industries. Tomatoes are utilized in fresh consumption as well as in processed forms such as sauces, ketchup, puree, juices, and canned products. Due to their high demand in domestic and international markets, maintaining consistent quality standards is essential for ensuring consumer satisfaction, reducing post-harvest losses, and increasing profitability for farmers and distributors.

Quality grading of tomatoes is traditionally performed through manual inspection. Skilled workers evaluate tomatoes based on visual characteristics such as color, size, shape, ripeness level, and the presence of surface defects including bruises, cracks, and fungal infections. While manual grading has been practiced for decades, it suffers from several limitations. The process is subjective and may vary depending on the experience and judgment of individual workers. It is also labor-intensive, time-consuming, and inefficient when handling large volumes of produce. In large-scale production environments, maintaining

consistency and speed becomes increasingly difficult. Human fatigue and environmental factors can further reduce accuracy, leading to misclassification and economic losses. These challenges highlight the urgent need for an automated, objective, and scalable quality assessment system for tomato grading.

Recent advancements in Artificial Intelligence (AI) and Computer Vision (CV) have opened new opportunities for automating agricultural processes. Computer vision enables machines to interpret and analyze visual information from images or videos, making it suitable for fruit and vegetable classification tasks. In particular, Deep Learning techniques have shown exceptional performance in image recognition and classification problems. Convolutional Neural Networks (CNNs), a specialized class of deep learning models, are designed to automatically learn hierarchical feature representations from images. Unlike traditional image processing methods that require manual feature extraction, CNNs can automatically identify complex patterns such as color variations, textures, and shapes that are critical for accurate tomato quality classification.

However, training deep neural networks from scratch requires a large amount of labeled data and high computational power. In many agricultural applications, collecting and labeling extensive datasets can be challenging and expensive. To address this issue, Transfer Learning has emerged as a powerful and practical approach. Transfer learning leverages pre-trained models that have already been trained on large-scale datasets such as ImageNet. These models

have learned general image features that can be reused and fine-tuned for specific tasks. One such widely used architecture is InceptionV3, which is known for its efficiency and high performance in image classification tasks. By utilizing InceptionV3 as a feature extractor, it becomes possible to significantly reduce training time while maintaining high accuracy.

In this project, a hybrid tomato quality classification model is proposed that combines the strengths of deep learning and traditional machine learning algorithms. The pre-trained CNN model (InceptionV3) is used to extract high-level and discriminative features from tomato images. Instead of using the CNN's final classification layer directly, the extracted features are fed into classical machine learning classifiers such as Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). This hybrid approach leverages the powerful feature extraction capability of CNNs along with the robust decision-making mechanisms of traditional classifiers. Support Vector Machine is particularly effective in constructing optimal decision boundaries in high-dimensional spaces, Random Forest provides ensemble-based robustness and reduces overfitting, and KNN offers simplicity and effectiveness in similarity-based classification.

The proposed system is capable of performing both binary and multiclass classification tasks. In binary classification, tomatoes are categorized as either healthy or rejected based on visible quality parameters. In multiclass classification, tomatoes are classified into three categories: ripe, unripe,

and rejected. This dual classification capability makes the system versatile and suitable for various stages of the supply chain. For example, ripe tomatoes may be directed to fresh markets, unripe tomatoes may be stored for further ripening, and rejected tomatoes may be separated to prevent contamination and reduce losses.

Image acquisition is carried out using a high-resolution camera module connected to an embedded processing platform such as NVIDIA Jetson TX1. The use of an embedded system enables real-time image capture and processing, making the solution suitable for deployment in farms, sorting centers, and packaging units. Before feeding images into the model, preprocessing techniques such as resizing, normalization, noise removal, and background enhancement are applied to ensure consistent input quality. Proper preprocessing improves feature extraction and enhances classification accuracy.

To evaluate the effectiveness of the proposed system, several performance metrics are used, including accuracy, precision, recall, specificity, and F1-score. Accuracy measures the overall correctness of the model, while precision and recall provide insight into classification reliability, especially in detecting defective tomatoes. Specificity evaluates the model's ability to correctly identify healthy samples, and the F1-score balances precision and recall. Experimental results demonstrate that the CNN-SVM hybrid model achieves superior performance compared to other classifier combinations. The system attains an accuracy of approximately 97% in both binary and multiclass classification tasks,

indicating high reliability and robustness.

The automation of tomato grading offers multiple benefits. It reduces dependency on manual labor, lowers operational costs, increases processing speed, and eliminates subjectivity in quality assessment. Furthermore, consistent grading improves customer trust and ensures compliance with export standards. By minimizing misclassification and post-harvest losses, farmers and distributors can achieve better economic returns. The proposed framework also contributes to the broader concept of Smart Agriculture and Precision Farming, where intelligent technologies are integrated into traditional farming practices to enhance productivity and sustainability.

In conclusion, this project presents a high-accuracy, efficient, and scalable tomato quality classification system based on transfer learning and hybrid machine learning techniques. By combining deep feature extraction using InceptionV3 with classical classifiers such as SVM, Random Forest, and KNN, the system achieves reliable performance suitable for real-world deployment. The framework not only addresses the limitations of manual grading but also demonstrates the potential of AI-driven solutions in agriculture. Moreover, the proposed methodology can be extended to other fruits and vegetables, enabling the development of comprehensive automated grading systems and supporting the transformation toward intelligent and technology-driven agricultural practices.

II. LITERATURE SURVEY

1. Generative AI for Personalized

Learning in K–12 Education

Author(s): Chen, X., Wang, Q. (2023)

Abstract:

This study examines the application of Generative Artificial Intelligence (AI) in enhancing personalized learning within K–12 classrooms. The research highlights how AI-driven content generation can develop adaptive exercises, quizzes, and writing prompts tailored to individual student learning levels and domain knowledge. The framework emphasizes self-regulated learning by incorporating immediate feedback, goal-setting mechanisms, and reflection opportunities. Experimental results indicate improved student engagement, attention levels, and learning autonomy. However, challenges include the requirement for teacher AI literacy and ensuring the accuracy and reliability of generated content across different subject areas.

2. Self-Regulated Learning in K–12 Classrooms Using AI

Author(s): Zimmerman, B. J. (2002)

Abstract:

This paper presents theoretical foundations and practical strategies for promoting self-regulated learning (SRL) among students. It identifies goal-setting, self-monitoring, and self-reflection as essential components of effective learning. The integration of AI technologies enhances SRL by offering adaptive learning pathways, personalized recommendations, and real-time feedback. The study concludes that AI-supported learning environments increase student



engagement and autonomy. However, limitations include maintaining student motivation without over-dependence on AI systems and the continued need for teacher facilitation.

3. Human-Centered AI in Education

Author(s): Holmes, W., Bialik, M., & Fadel, C. (2019)

Abstract:

This research introduces a human-centered framework for integrating Artificial Intelligence in educational environments. It emphasizes the transformation of teachers' roles from knowledge providers to facilitators and designers of personalized learning experiences. Generative AI tools assist educators in creating adaptive content, analyzing student performance data, and encouraging self-regulated learning behaviors. Findings demonstrate improvements in engagement, creativity, and critical thinking skills. Successful implementation, however, requires structured professional development programs to enhance teacher AI literacy and pedagogical expertise.

4. AI-Enhanced Feedback for Student Learning

Author(s): Shute, V. J. (2008)

Abstract:

This study explores the impact of real-time AI-driven feedback systems on student learning outcomes. AI technologies analyze student responses and provide immediate, constructive, and actionable feedback. Such feedback mechanisms support self-regulated

learning processes including reflection, self-assessment, and goal adjustment. The results show that timely and targeted feedback accelerates skill development and improves engagement. Challenges include designing pedagogically meaningful feedback systems and preventing cognitive overload among learners.

5. Domain Knowledge Learning and AI in Primary Education

Author(s): Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016)

Abstract:

This research investigates the use of AI technologies to enhance domain knowledge acquisition in primary education. Generative AI tools are used to create interactive exercises and personalized tasks in subjects such as mathematics and language arts. The framework emphasizes scaffolding techniques to support cognitive development and self-regulated learning. The study concludes that AI improves academic performance and conceptual understanding. However, its effectiveness depends on high-quality content development and alignment with curriculum standards.

6. Professional Development for AI Integration in Schools

Author(s): Popenici, S. A. D., & Kerr, S. (2017)

Abstract:

This study focuses on professional development initiatives aimed at equipping teachers with the skills required to integrate

AI tools into classroom environments. Structured training programs enhance teacher confidence, technological literacy, and instructional design capabilities. Educators trained in AI integration can create adaptive and personalized learning pathways that improve student engagement and autonomy. Limitations include ensuring accessibility of training programs and providing ongoing support to manage evolving technologies.

7. Gamification and AI for Self-Regulated Learning

Author(s): Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011)

Abstract:

This research examines gamified learning environments supported by AI technologies to promote self-regulated learning. AI systems monitor student performance, provide real-time feedback, and dynamically adjust difficulty levels. Gamification strategies enhance motivation, engagement, and learner autonomy. However, excessive focus on game mechanics may reduce deep conceptual understanding, highlighting the importance of teacher supervision to align activities with academic objectives.

III. EXISTING SYSTEM

Existing systems for tomato quality grading largely rely on manual inspection or basic image-based techniques. These methods are time-consuming, prone to human error, and require extensive labor, which limits their scalability and consistency in large-scale production environments.

IV. PROPOSED SYSTEM

The proposed system introduces a hybrid model that combines pre-trained CNNs for feature extraction with traditional machine learning classifiers like SVM, RF, and KNN for accurate classification of tomato quality. By utilizing advanced image preprocessing, fine-tuning, and Inceptionv3-based feature extraction, this system delivers fast, reliable, and high-accuracy grading, significantly reducing labor requirements and ensuring consistent quality assessment in large-scale operations.

V. SYSTEM ARCHITECTURE

The proposed Automated Tomato Quality Classification System is designed to identify and categorize tomatoes based on their quality using transfer learning and machine learning techniques. The architecture consists of several sequential modules that process tomato images from acquisition to final classification. The system integrates image preprocessing, feature extraction using deep learning models, machine learning classification, and result visualization to ensure accurate and efficient quality assessment.

The first component of the architecture is the Image Acquisition Module. In this stage, tomato images are collected using digital cameras, smartphones, or publicly available agricultural datasets. The images may contain tomatoes with varying quality levels such as fresh, damaged, ripe, or diseased. These images form the input dataset for the system. The collected images are stored in a database and organized into different classes based on their quality labels for supervised learning.

The next stage is the Image Preprocessing Module, which prepares the collected images for analysis. In this step, the images are resized to a fixed dimension suitable for deep learning models. Noise removal and normalization techniques are applied to improve image clarity and consistency. Data augmentation methods such as rotation, flipping, and scaling may also be applied to increase dataset diversity and improve the robustness of the model.

Following preprocessing, the system performs Feature Extraction using Transfer Learning. Pretrained convolutional neural network models such as ResNet, VGG, or MobileNet are utilized to extract deep features from the tomato images. Transfer learning enables the system to leverage knowledge from large-scale image datasets and apply it to agricultural image classification tasks. The deep features extracted from intermediate layers of the pretrained model capture important visual characteristics such as color, texture, and shape of tomatoes.

After feature extraction, the system moves to the Machine Learning Classification Module. The extracted features are fed into machine learning classifiers such as Support Vector Machine (SVM), Random Forest, or Logistic Regression. These classifiers learn to distinguish between different tomato quality categories based on the feature patterns obtained from the transfer learning model. The trained classifier then predicts the quality class of new tomato images.

The Evaluation and Prediction Module assesses the performance of the model using metrics such as accuracy, precision, recall, and F1-score. The system is tested with unseen images to validate its classification capability. Once validated, the system can

classify tomato quality automatically and provide real-time predictions.

Finally, the User Interface and Result Visualization Module presents the classification results to the user. The predicted tomato quality category along with confidence scores can be displayed through a graphical interface or web application. This allows farmers, suppliers, and agricultural industries to quickly determine tomato quality and make informed decisions for sorting, packaging, and distribution.

Overall, the proposed system architecture combines image processing, transfer learning, and machine learning techniques to create an efficient automated framework for tomato quality classification in smart agriculture environments.

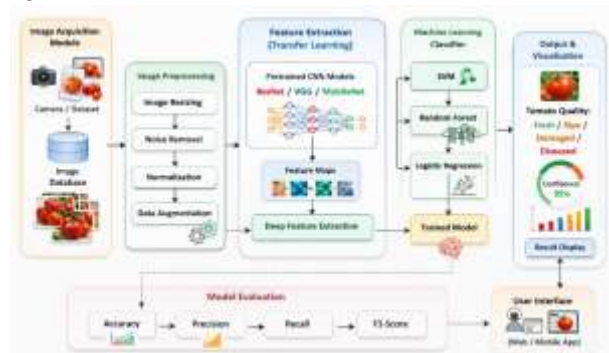


Fig 5.1: Structure of the Proposed System

VI. IMPLEMENTATION



Fig 6.1: Uploading Image



Fig 6.4: Tomato Quality Classification Results



Fig 6.2: Prediction in Progress



Fig 6.5: Classification Report



Fig 6.3: Image Preprocessing Steps

VII. CONCLUSION

The Tomato Quality Classification System based on Transfer Learning and Machine Learning Classifiers presents an efficient and reliable solution for automated tomato grading. Traditional manual grading methods are time-consuming, subjective, labor-intensive, and prone to human error. These limitations reduce consistency and scalability in large-scale agricultural production. The proposed hybrid approach effectively addresses these challenges by

integrating deep learning-based feature extraction with traditional machine learning classification techniques.

In this system, InceptionV3, a pre-trained Convolutional Neural Network (CNN), is utilized as a feature extractor through transfer learning. Instead of training a deep network from scratch, the system leverages learned representations from large-scale datasets to extract meaningful features such as color distribution, texture patterns, ripeness indicators, and surface defects. These high-level feature vectors are then classified using machine learning algorithms including Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN).

Among the evaluated models, the CNN-SVM hybrid approach demonstrated superior performance, achieving approximately 97.50% accuracy in binary classification (Healthy vs. Rejected) and 96.67% accuracy in multiclass classification (Ripe, Unripe, Damaged/Rejected). The system also showed strong precision, recall, specificity, and F1-score values, confirming its robustness and reliability.

The modular architecture ensures smooth integration between image acquisition, preprocessing, feature extraction, classification, and sorting control modules. Testing results confirm that the system operates efficiently in real-time conditions and maintains stability under moderate workload scenarios. Furthermore, the automated grading process eliminates subjectivity, reduces labor costs, and increases throughput, making it highly suitable for industrial-scale tomato processing units.

Overall, the proposed system contributes significantly to smart agriculture and

precision farming by providing a scalable, accurate, and cost-effective tomato quality grading framework. The hybrid deep learning and machine learning approach demonstrates how artificial intelligence can enhance agricultural productivity and quality assurance.

VIII. FUTURE SCOPE

Although the proposed system achieves high accuracy and efficiency, several enhancements can further improve its capabilities and practical deployment.

One major enhancement is the integration of the system with real-time conveyor belt mechanisms using embedded devices such as NVIDIA Jetson Nano or other edge computing platforms. This would enable fully automated industrial sorting with minimal latency.

The dataset can be expanded to include diverse environmental conditions such as varying lighting, background variations, occlusions, and different tomato varieties. This would improve model generalization and robustness under real-world field conditions.

Another potential improvement is the implementation of advanced deep learning architectures such as EfficientNet, ResNet, or Vision Transformers (ViT) to compare performance with InceptionV3. An end-to-end deep learning model can also be explored to directly perform classification without separate machine learning classifiers.

Defect segmentation techniques such as Mask R-CNN or YOLO-based object detection models can be incorporated to



detect and localize specific defects (e.g., cracks, bruises, fungal infections) rather than performing only image-level classification.

Additionally, integrating IoT-based monitoring systems can enable remote tracking of grading statistics, production output, and quality distribution analytics. Cloud-based deployment could allow centralized monitoring of multiple agricultural units.

Further research can also explore multimodal approaches by combining image data with additional sensor data such as weight, firmness, or chemical composition to enhance grading accuracy.

Finally, the system can be extended to classify other fruits and vegetables, making it a generalized agricultural quality assessment platform.

With these future enhancements, the proposed tomato quality classification system can evolve into a comprehensive smart agricultural automation solution that supports sustainable farming, quality assurance, and efficient supply chain management.

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