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Fruit Grade Classification and Disease Detection using Deep Learning Techniques

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Abstract— Ensuring optimal food quality and agricultural productivity hinges on effective fruit quality assessment and disease detection. Introducing a comprehensive strategy employing deep learning techniques to address critical aspects of fruit quality assessment and disease detection in agriculture. The methodology is structured into two distinct phases, each designed to optimize the accuracy and efficiency of the overall system. In the initial phase, image acquisition, preprocessing, and precise Region of Interest (ROI) detection using the Expectation-Maximization (EM) method lay the foundation for fruit classification with the AlexNet architecture. Rigorous training and testing procedures ensure the model's efficacy. The subsequent phase extends the initial process, with a heightened focus on feature extraction facilitated by DenseNet201. Thorough performance analysis, incorporating multiple metrics, assesses the accuracy and effectiveness of the system. This framework aspires to establish a robust solution for automated fruit grading and disease detection. By harnessing the capabilities of deep learning models, the goal is to accurately classify fruits and identify potential diseases, contributing significantly to agricultural practices and food quality management. The anticipated outcomes aim to set the groundwork for future advancements in the agricultural sector, providing a technological solution that enhances efficiency in fruit quality assessment and disease detection, ultimately benefiting food quality and crop yield.

Keywords- Deep Learning, Fruit Disease Detection, Agricultural Advancement, Expectation-Maximization (EM) Method, AlexNet Architecture, DenseNet201, MATLAB

I. INTRODUCTION

A. *Overview*

This paper presents an integrated approach utilizing deep learning techniques to revolutionize fruit quality assessment and disease detection in agriculture. The methodology encompasses two pivotal stages, where advanced image processing techniques and state-of-the-art deep learning models are employed for optimal results. In the initial stage, we explore image acquisition and preprocessing, incorporating sophisticated methods such as noise removal and precise resizing. The Expectation-Maximization (EM) method is then applied for accurate Region of Interest (ROI) detection, followed by fruit classification using the robust AlexNet architecture. Rigorous training and testing procedures ensure the model's effectiveness in accurately categorizing fruits. The subsequent stage builds upon the initial framework, emphasizing feature extraction through DenseNet201. A comparative analysis is conducted to evaluate and compare the performance of the AlexNet and DenseNet201 models. Various metrics are employed, providing a comprehensive assessment of the system's accuracy and efficiency. The research eliminates the need for traditional methods and integrates deep learning for optimal fruit quality assessment and disease detection. This journal contributes to the advancement of agricultural practices and food quality management by presenting a holistic framework that enhances efficiency in automated fruit grading and disease detection. The outcomes aim to pave the way for future technological solutions that positively impact crop yield and overall food quality

B. *History*

This journal provides a comprehensive overview of recent advancements in fruit classification and disease detection using various methodologies. Notable methodologies include the integration of deep learning models, such as Mask R-CNN, AlexNet-SPP, and DenseNet201, for precise fruit grading. The exploration of hybridized approaches combining backpropagation neural networks (BPNN) and discriminant analyzers demonstrates enhanced classification accuracy. Novel methodologies like fractional fuzzy two-dimensional linear discriminant analysis (FF2DLDA) showcase improvements in pomegranate fruit grading. The introduction of an image-based deep learning sorting system utilizing convolutional neural networks (CNNs) exemplifies the potential for automated date fruit classification. Disease detection methodologies encompass deep convolutional neural networks, including Faster R- CNN, with adaptations for multi-modal imaging, and comparative studies between traditional machine learning and deep learning approaches. The history presented reflects a dynamic landscape of methodologies driving advancements in fruit classification and disease detection.

C. *Applications*

The proposed deep learning framework presents a transformative application potential across diverse sectors. In agriculture, it promises to revolutionize fruit grading accuracy, empowering farmers with precise quality assessments for optimal market positioning. Simultaneously, its disease detection capabilities offer early intervention, safeguarding crop yields. Beyond agriculture, the framework's adaptability extends to automated sorting in commercial settings, enhancing supply chain efficiency. Its standardized approach also positions it as a valuable tool in research, fostering innovation in food quality, agricultural practices, and crop management. This comprehensive application spectrum underscores its potential to reshape industries, advancing efficiency, quality, and resilient.

II. EXISTING METHOD

The existing methodology for mango detection, as presented in a recent paper, combines cutting-edge techniques to address the intricate challenge of accurately categorizing mangoes. This intelligent mango fruit grade classification system employs a two-module approach, featuring an Object Segmentation Module and an Image Preprocessing Module. The Object Segmentation Module utilizes the Mask R-CNN model for precise mango shape delineation and bounding box generation. This step ensures accurate identification of mangoes, addressing their complex appearance and susceptibility to image noise. The Image Preprocessing Module then enhances image quality based on the derived information, focusing exclusively on the mango fruit. The classification model is built upon the AlexNet-SPP architecture, incorporating a Spatial Pyramid Pooling (SPP) layer tailored for varying mango sizes. The system undergoes rigorous evaluation with a dataset comprising 1000 mango images, demonstrating an impressive 97.5% accuracy. The integration of Mask R-CNN and AlexNet-SPP proves promising for revolutionizing mango grading practices, offering heightened efficiency, accuracy, and cost reduction. This methodology showcases a holistic approach, combining advanced segmentation, preprocessing, and classification techniques to address the specific challenges posed by mango fruit detection in diverse environmental conditions[1].

III. PROPOSED METHOD

The proposed methodology involves training and comparing two deep learning models, specifically AlexNet and DenseNet201, for fruit grade classification and disease detection. In the initial phase, a meticulous image acquisition process is undertaken, followed by preprocessing steps such as resizing and color conversion to optimize input data for both models. Region of Interest (ROI) detection is performed using the Expectation-Maximization (EM) method, ensuring precise localization of relevant fruit regions in the images.

For the first model, AlexNet is employed for classification after ROI detection. Rigorous training and testing procedures are executed to optimize the model's parameters and evaluate its performance on a diverse dataset. Simultaneously, the second model utilizes DenseNet201, focusing on feature extraction for specific fruit classification and disease detection tasks. Similar training and testing procedures are applied to ensure the effectiveness of DenseNet201.

Figure 1: Architecture of the proposed method

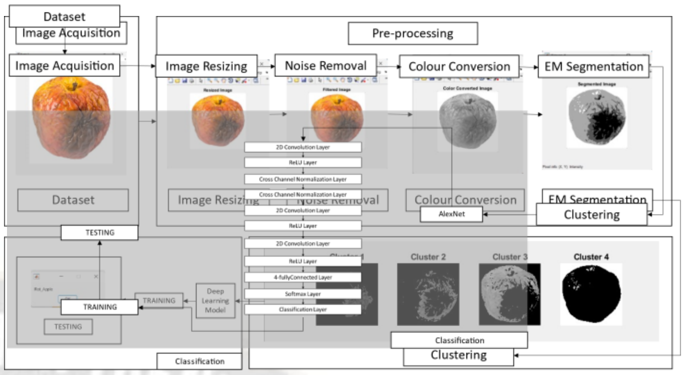

Figure 2: Architecture of the proposed method using AlexNet

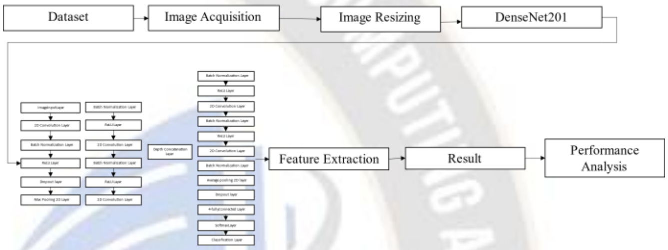

Figure 3: Architecture of the proposed method using DenseNet201

The performance of both models is comprehensively analyzed using various metrics, including accuracy, error rate, sensitivity, specificity, precision, false positive rate, F1 score, Matthews correlation coefficient, and Kappa. This comparative analysis aims to highlight the strengths and weaknesses of each model, providing insights into their suitability for fruit grade classification and disease detection tasks. The proposed methodology integrates advanced deep learning architectures and thorough performance evaluation, contributing to the enhancement of automated fruit quality assessment systems.

Figure 4: Image Samples

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IV. IMPLEMENTATION

A. *Image acquisition*

The initial phase of image processing commences with image acquisition, where digital images of various fruits are captured to form the dataset. These images, stored in RGB format, are saved in a designated folder for subsequent processing. The dataset encompasses diverse fruit images intended for segmentation. To facilitate further analysis, the stored images are then processed using MATLAB. This systematic approach ensures that a comprehensive set of fruit images is readily available for subsequent stages of the image processing pipeline.

B. *Image Pre-processing*

Moving to the next stage, Image Pre-processing involves refining the acquired fruit images stored in the designated folder. The RGB images are subjected to a series of operations to enhance their quality and prepare them for subsequent analyses. Techniques such as resizing and color conversion are applied to standardize the input data for optimal processing. The processed images are then saved for further stages in the image processing pipeline. This meticulous pre-processing step ensures that the input data is appropriately formatted, minimizing noise and variations, and facilitating more effective analysis and feature extraction in subsequent phases. The refined images serve as the foundation for accurate Region of Interest (ROI) detection and subsequent classification tasks in the overall framework.

C. *Image Segmentation*

In the image segmentation stage, the pre-processed fruit images, stored in the designated folder, undergo a precise analysis to identify and delineate specific regions of interest (ROIs). Employing sophisticated techniques such as the Expectation-Maximization (EM) method, the system accurately segments and isolates the relevant portions of the fruit images. This method ensures the precise localization of fruit boundaries, allowing for focused analysis on key areas. The Expectation-Maximization (EM) algorithm involves iterative steps of expectation (E-step) and maximization (M-step). The basic equations for the EM algorithm can be outlined as follows:

1) *Expectation (E-step):*

$$\mathrm{E}(\theta) = \mathbb{E}_{\theta_k}[\log p(X, Z|\theta)] \quad (1)$$

This step calculates the expected value of the log-likelihood function given the observed data X and the current parameter estimates θ , where Z represents the latent variables.

2) *Maximization (M-step):*

$$\theta_{k+1} = \arg\max_{\theta} E(\theta) \quad (2)$$

In the maximization step, the algorithm maximizes the expected log-likelihood with respect to the model parameters θ, updating the parameter estimates for the next iteration.

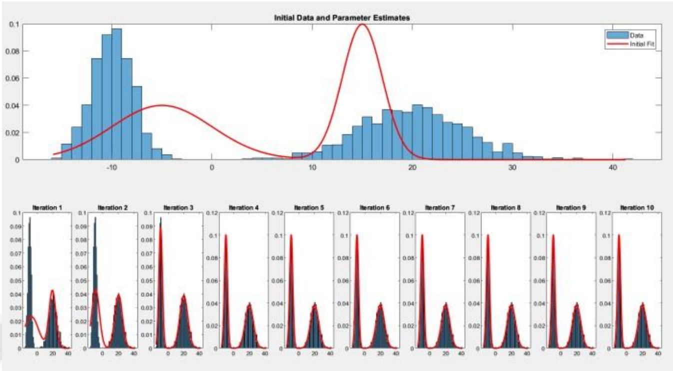

Figure 5: EM Samples

The outcome of the segmentation process is a set of delineated ROIs, each representing a distinct fruit within the image. These segmented regions serve as the foundation for subsequent tasks such as feature extraction and classification. The use of advanced segmentation techniques enhances the system's ability to precisely identify and isolate individual fruits, contributing to the overall accuracy and effectiveness of the fruit grading and disease detection system.

D. *Classification*

In the classification stage, the segmented regions of interest (ROIs) undergo a comprehensive analysis using two distinct deep learning models: AlexNet and DenseNet201.

1) *AlexNet*:

The AlexNet model, renowned for its effectiveness in image classification tasks, is employed for the classification of segmented fruit regions. Through meticulous training and testing procedures on a diverse dataset, AlexNet optimizes its parameters to accurately categorize the identified fruits. The model's robust architecture, including a Spatial Pyramid Pooling (SPP) layer, facilitates precise classification tailored to varying fruit sizes. The comprehensive evaluation of the AlexNet model involves assessing various performance metrics, including accuracy, error rate, sensitivity, specificity, precision, false positive rate, F1 score, Matthews correlation coefficient, and Kappa.

2) *DenseNet201*:

Simultaneously, the DenseNet201 model is utilized for fruit classification within the segmented ROIs. This model emphasizes feature extraction through dense connections between layers, enhancing its ability to capture intricate patterns. Employing transfer learning, the pre-trained DenseNet201 model is optimized for specific fruit classification and disease detection tasks. Similar to the AlexNet analysis, the evaluation of DenseNet201 involves a thorough examination of performance metrics, providing insights into its effectiveness for fruit grading.

The separate analyses of the AlexNet and DenseNet201 models aim to discern their individual strengths and weaknesses in the context of fruit classification, contributing to a comprehensive understanding of their respective performances within the automated system.

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E. Feature Extraction

In the feature extraction stage, the segmented regions of interest (ROIs), previously identified through image segmentation, undergo a process to capture relevant and distinctive characteristics that can effectively represent the fruit's visual information. Feature extraction is crucial for providing meaningful input to the classification models. For DenseNet201, a deep learning model, this stage involves leveraging the pre-trained network to automatically extract hierarchical and discriminative features from the segmented ROIs. DenseNet201's dense connectivity facilitates the efficient flow of information between layers, enabling the model to capture intricate patterns and nuances within the fruit images. Additionally, traditional feature extraction methods may be employed, encompassing statistical measures, texture descriptors, and color-based features. These extracted features serve as informative descriptors that contribute to the discriminative power of the classification models.

The combined use of deep learning-based feature extraction with models like DenseNet201 and traditional methods ensures a comprehensive representation of the visual characteristics of the fruit images. This diverse set of features enhances the system's ability to accurately classify fruits and detect potential diseases based on a rich set of discriminative information.

F. Performance Metrics

In the evaluation of the proposed fruit classification system utilizing the AlexNet and DenseNet201 models, a comprehensive set of performance metrics is employed. These metrics serve as crucial benchmarks for assessing the efficacy of the models in accurately categorizing fruits within the segmented regions of interest (ROIs). The following performance metrics are utilized for a thorough analysis:

a) *Accuracy:* Measures the overall correctness of fruit classification.
b) *Error Rate*: Complements accuracy, indicating the proportion of misclassifications.
c) *Sensitivity (Recall):* Gauges the models' ability to correctly identify positive instances among all actual positives.
d) *Specificity*: Assesses the models' capability to correctly identify negative instances among all actual negatives.
e) *Precision*: Examines the precision of the models in correctly identifying positive instances.
f) *False Positive Rate:* Measures the rate of instances incorrectly identified as positive among all actual negatives. *F1 Score*: Provides a balanced measure of precision and recall, particularly useful for imbalanced datasets.
g) *Matthews Correlation Coefficient (MCC):* Captures the correlation between predicted and actual classifications.
h) *Kappa Coefficient*: Evaluates the agreement between observed and expected classifications, considering chance agreement

These performance metrics collectively offer a comprehensive evaluation of the fruit classification system, shedding light on the strengths and areas for improvement of both the AlexNet and DenseNet201 models. The results presented in the paper will contribute valuable insights into the models' performance and their suitability for automated fruit grading applications.

V. Results and Discussion

A. Simulation output for Disease Classification

In the simulation output for Disease Classification, a stepwise depiction of the image processing stages is presented to elucidate the methodology's effectiveness. The initial input image is showcased, followed by a representation of the image resized to a standardized 224x224 pixel dimension, optimizing it for subsequent analysis. The grayscale transformation simplifies the image, facilitating focused processing. The segmented image, highlighting regions of interest, is then displayed, providing insight into areas potentially affected by disease. Further refinement is achieved through the identification and visualization of four distinct clusters, aiding in pattern recognition associated with different disease indications.

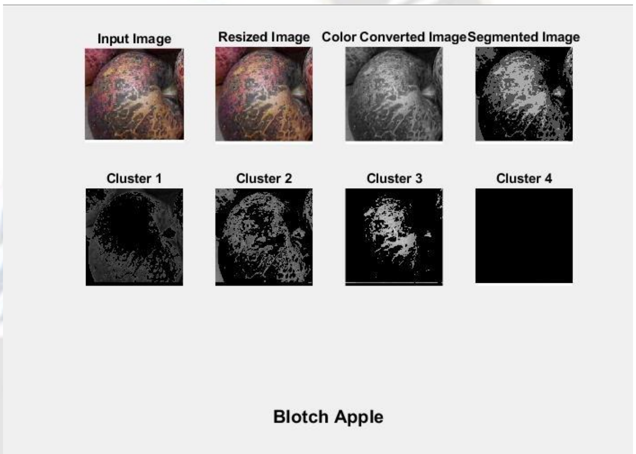

Figure 6: Comprehensive Disease Classification Output for Blotch Apple

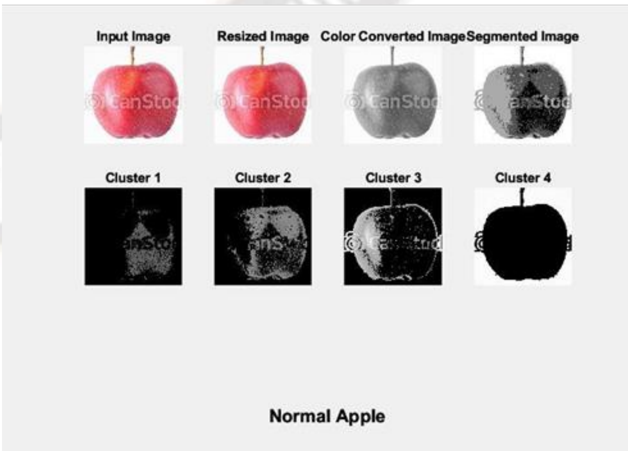

Figure 7: Comprehensive Disease Classification Output for Normal Apple

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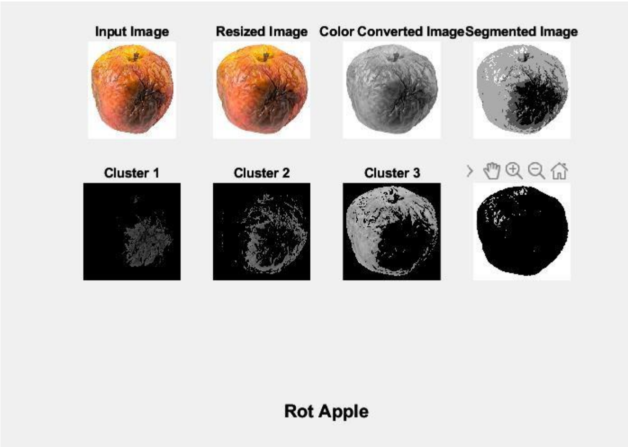

Figure 7: Comprehensive Disease Classification Output for Rot Apple

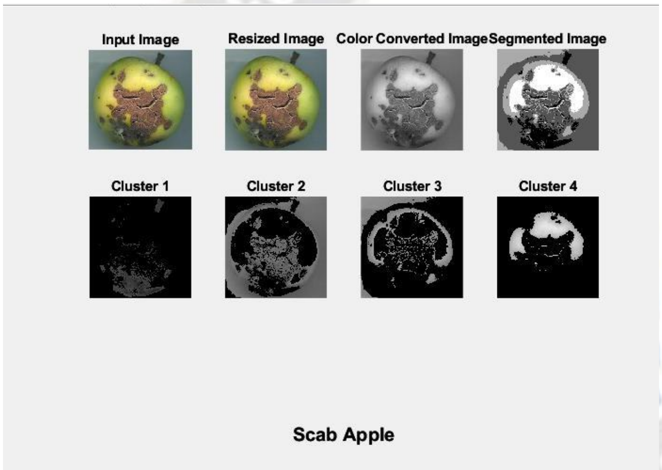

Figure 7: Comprehensive Disease Classification Output for Scab Apple

Complementing the visual representation, a classification string succinctly conveys the outcome of the disease classification process. Additionally, the simulation output incorporates essential performance parameters, including accuracy, sensitivity, specificity, precision, false positive rate, F1 score, Matthews correlation coefficient, and Kappa coefficient. These metrics quantitatively evaluate the model's ability to accurately classify diseases. This holistic output approach not only offers a clear visual narrative but also provides researchers and practitioners with the quantitative measures needed to assess the reliability and efficiency of the disease classification system.

B. *Performance Metrics*

TABLE I. PERFORMANCE METRICS

Parameters	Performance Metrics-AlexNet	Performance Metrics - DenseNet201
Accuracy	0.9471	0.9566
Error Rate	0.0519	0.0345
Sensitivity	0.9560	0.9686
Specificity	0.7333	0.9890
Precision	0.9560	0.9659
FPR	0.1833	0.0110
F1 Score	0.9560	0.9655
MCC	0.6982	0.9556
Kappa	0.7512	0.9080

The performance metrics of disease classification using the AlexNet and DenseNet201 models reveals valuable insights into their respective capabilities. The accuracy of the models stands at 94.71% for AlexNet and slightly higher at 95.66% for DenseNet201, indicating a commendable overall classification performance. The error rate is notably lower for DenseNet201 (3.45%) compared to AlexNet (5.19%), highlighting a superior precision in disease identification by the DenseNet201 model. Sensitivity, reflecting the ability to correctly identify positive instances, is also higher for DenseNet201 (96.86%) compared to AlexNet (95.60%). Specificity, denoting the accurate identification of negative instances, exhibits a substantial improvement in DenseNet201 (98.90%) over AlexNet (73.33%). Precision, F1 score, and Matthews correlation coefficient further affirms the superior performance of DenseNet201. Despite a slightly lower Kappa coefficient, DenseNet201 demonstrates a remarkable overall proficiency in disease classification, emphasizing its potential for enhanced accuracy and reliability in practical applications.

C. *Future Work*

In envisioning future work for the presented journal, several avenues emerge for advancing and refining the proposed disease classification system based on deep learning models. Firstly, expanding the dataset to encompass a more extensive variety of fruit diseases and diverse environmental conditions would enhance the models' robustness and generalization capabilities. Additionally, investigating the integration of transfer learning techniques and exploring other state-of-the-art architectures could further optimize the models' performance. The incorporation of explainable AI methodologies, such as attention mechanisms, may provide valuable insights into the decision-making processes of the models, fostering transparency and interpretability. Moreover, real-world deployment and validation of the system in different agricultural settings would contribute to its practical utility and reliability. Collaborative efforts with domain experts, agronomists, and stakeholders can facilitate the incorporation of domain-specific knowledge, ensuring the system's alignment with the dynamic challenges of the agricultural sector. Lastly, considerations for scalability and computational efficiency should be addressed, paving the way for the implementation of the system in real-time applications and resource-constrained environments. This future work aims to fortify the system's efficacy, widen its applicability, and contribute to the ongoing evolution of automated disease detection in agriculture.

VI. CONCLUSIONS

In conclusion, the presented framework offers a robust solution for automated fruit disease classification, leveraging advanced deep learning models—specifically, AlexNet and DenseNet201. The system demonstrates notable accuracy and efficiency in identifying and categorizing diseases affecting fruits, with DenseNet201 showcasing superior performance across key metrics. The performance analysis highlights the practical potential of the system in enhancing crop health monitoring and disease management in agriculture. Looking ahead, future work is crucial to fortify the system's adaptability, transparency, and scalability. This involves incorporating a more diverse dataset, exploring advanced model architectures, and collaborating with domain experts. Real- world deployment and validation will be pivotal for bridging the gap between research and practical agricultural applications. Ultimately, this work contributes to ongoing initiatives in precision agriculture, aiming to empower farmers with cutting-edge technology for early disease detection and informed decision-making. As technology evolves, the presented framework holds promise in revolutionizing disease management practices, fostering sustainable and resilient agricultural systems.

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