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Original Article

Transfer Learning For Fruit Detection

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Abstract *- In recent years, increasing awareness of healthy diets has led to a growing demand for high-quality and fresh fruits, making accurate fruit detection and freshness assessment essential in agriculture and food supply chains. However, traditional manual inspection methods are time-consuming, labor-intensive, and prone to human error, especially when handling large volumes of produce. To address this problem, this study proposes an automated image-based fruit detection approach using transfer learning. The method employs a pre-trained VGG19 convolutional neural network for feature extraction, followed by a Softmax classifier to categorize fruits such as apples, bananas, and oranges based on freshness. Image preprocessing techniques including resizing and normalization are applied to enhance model robustness. Experimental results demonstrate that the VGG19-based model achieves high classification accuracy and outperforms several existing approaches, confirming its effectiveness in fruit detection tasks. In conclusion, the proposed system provides a reliable and efficient solution for automated fruit freshness classification and shows strong potential for real-world applications in smart agriculture, quality inspection, and retail automation.*

Keywords *- Transfer Learning, Vgg19, Deep Learning, CNN, Image Classification, Computer Vision, Smart Agriculture.*

1. Introduction

In recent years, the consumption of fruits has increased substantially due to rising awareness of their nutritional value and role in maintaining a healthy lifestyle. Fruits are rich in essential vitamins, minerals, antioxidants, and dietary fiber, making their quality and freshness critical for human health. In agriculture, food processing, and retail industries, accurate detection and classification of fruits are essential for quality assurance, inventory management, and automated harvesting systems. Traditional manual methods of fruit identification and sorting are labor-intensive, time-consuming, and susceptible to human error, especially when handling large volumes of produce. These limitations necessitate the development of automated and intelligent fruit detection systems.

With advancements in computer vision and artificial intelligence, image-based fruit detection has gained significant attention. Deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in visual recognition tasks by automatically learning hierarchical features from images. CNN-based models can effectively capture complex visual patterns such as color, texture, and shape, which are crucial for distinguishing between different fruit types. However, training deep learning models from scratch requires extensive labeled datasets and high computational resources, which may not always be feasible in real-world applications.

Transfer learning has emerged as a powerful approach to address these challenges by leveraging pre-trained deep learning models trained on large and diverse datasets such as ImageNet. In transfer learning, the knowledge gained from solving a related task is reused and fine-tuned for a new target task, significantly reducing training time and data requirements. Pre-trained models such as VGG16, VGG19, ResNet, Inception, and MobileNet have shown strong generalization capabilities and are widely used for fruit detection and classification tasks. These models enable efficient feature extraction while maintaining high accuracy even with limited training data.

This research focuses on the application of transfer learning for fruit detection using the VGG19 architecture. The pre-trained VGG19 model is fine-tuned to detect and classify different fruit categories from input images, enabling accurate and reliable identification. The proposed system aims to improve detection performance, enhance robustness to variations in lighting and background, and support real-world applications such as automated harvesting, quality inspection, retail checkout systems, and smart agriculture. By leveraging transfer learning, this study demonstrates the effectiveness of deep learning techniques in developing scalable and efficient fruit detection solutions.

2. Literature Survey

Dadwal and Banga presented a review of color image segmentation techniques for fruit ripeness detection, highlighting methods such as thresholding and clustering based on color features. While these approaches can identify ripeness levels, they are sensitive to lighting variations and rely on handcrafted rules. The authors conclude that more adaptive and automated techniques are required for reliable fruit ripeness detection [1]. Ahmad et al. proposed a texture-based fruit detection method that uses texture feature extraction techniques to distinguish fruit regions from the background in images. The approach demonstrated improved detection performance compared to simple color-based methods, especially in cases where color alone was insufficient for accurate segmentation. However, the model’s reliance on handcrafted texture features limits its adaptability to varied fruit types and complex real-world conditions. The authors conclude that texture analysis can enhance fruit detection but suggest that more advanced feature learning methods are needed for robust performance across diverse datasets [2].

Nguyen et al. proposed a shape-based fruit detection approach that focuses on geometric features to identify fruits under varying conditions. The method addressed challenges such as occlusion and shape similarity, achieving reliable detection in controlled environments. However, its dependence on shape features limits robustness in complex backgrounds and varying viewpoints. The authors conclude that combining shape information with other features can improve fruit detection performance [3]. Zhang et al. proposed a convolutional neural network–based approach for fruit detection in natural environments, enabling automatic feature learning from images captured under varying lighting and background conditions. The model achieved improved detection accuracy compared to traditional feature-based methods. However, its performance depended on large labeled datasets and high computational resources. The authors conclude that CNNs are effective for fruit detection in real-world scenarios but can be further improved through optimization and transfer learning [4].

Manjulalayam et al. presented a comparative analysis of various deep learning architectures for activity recognition, showing that deep models outperform traditional methods in classification accuracy. However, the study focused on human activity data and did not address image-based detection tasks. The authors conclude that deep learning architectures are effective but must be adapted for domain-specific applications [5]. Simonyan and Zisserman proposed very deep convolutional neural networks (VGG) for large-scale image recognition, demonstrating that increasing network depth significantly improves classification accuracy. The VGG architecture achieved strong performance on the ImageNet dataset and became a foundation for many transfer learning applications. However, the model requires high computational resources. The authors conclude that deep CNN architectures are highly effective for visual recognition tasks [6].

Simonyan and Zisserman introduced the VGG network architecture, demonstrating that very deep convolutional neural networks with uniform small filters significantly improve image classification performance on large-scale datasets such as ImageNet. While the model achieved high accuracy and became widely adopted for feature extraction, its depth leads to increased computational and memory requirements. The authors conclude that deeper CNN architectures are highly effective for visual recognition tasks and form a strong foundation for transfer learning applications [7]. Sajid et al. utilized VGG-19–based transfer learning for automated fruit classification in smart agriculture, achieving improved classification accuracy compared to traditional methods. However, the study was evaluated on limited datasets, affecting generalization. The authors conclude that VGG-19 is effective for fruit classification in agricultural applications [8].

Wang et al. proposed a real-time fruit detection method using an optimized VGG19 model tailored for automated systems, demonstrating improved detection speed and accuracy in dynamic environments. However, the approach’s performance was primarily validated on specific datasets, which may limit generalizability to diverse real-world conditions. The authors conclude that optimized VGG19 architectures are effective for real-time fruit detection but further adaptation is needed for broader deployment [9]. Xiao et al. reviewed deep learning–based methods for fruit detection and recognition in automatic harvesting, reporting that CNN-based models achieve higher accuracy and robustness than traditional techniques. However, challenges such as occlusion, lighting variation, and limited datasets remain. The authors conclude that deep learning is effective for fruit detection but requires further improvement for real-world agricultural environments [10].

3. Methodology

The proposed system employs a transfer learning–based deep learning approach for fruit detection and freshness classification using the VGG19 convolutional neural network. Deep learning models, particularly CNNs, are well suited for image-based tasks because they automatically learn hierarchical features directly from raw image data, eliminating the need for manual feature extraction. Transfer learning further enhances this process by leveraging knowledge from models pre-trained on large datasets, thereby reducing training time and improving performance when limited task-specific data is available.

The overall architecture of the proposed model is illustrated in Figure 1, which depicts the complete processing pipeline from input fruit images to final freshness prediction. Initially, a labeled dataset of fruit images, including classes such as apples, bananas, and oranges, is collected. These images are preprocessed through resizing, normalization, and augmentation to improve robustness and generalization. Image preprocessing ensures uniform input dimensions and enhances the model’s ability to handle variations in lighting, orientation, and background.

After preprocessing, the images are passed to the VGG19 model, which serves as the feature extraction backbone. VGG19 consists of 16 convolutional layers and 3 fully connected layers, using small 3×3 convolutional filters and ReLU activation functions. As shown in Figure 3.3, the convolutional layers progressively extract low-level features such as edges and textures in the initial stages and higher-level semantic features in deeper layers. Max-pooling layers are used to reduce spatial dimensions while preserving important visual information. In the transfer learning setup, the convolutional base of VGG19 pre-trained on the ImageNet dataset is frozen to retain its learned generic image features. Custom fully connected layers are added on top of the base network to adapt the model to the fruit detection task. These layers transform the extracted features into a compact representation suitable for classification. The final layer employs a Softmax activation function to assign probability scores to each class, enabling accurate classification of fruits as fresh.

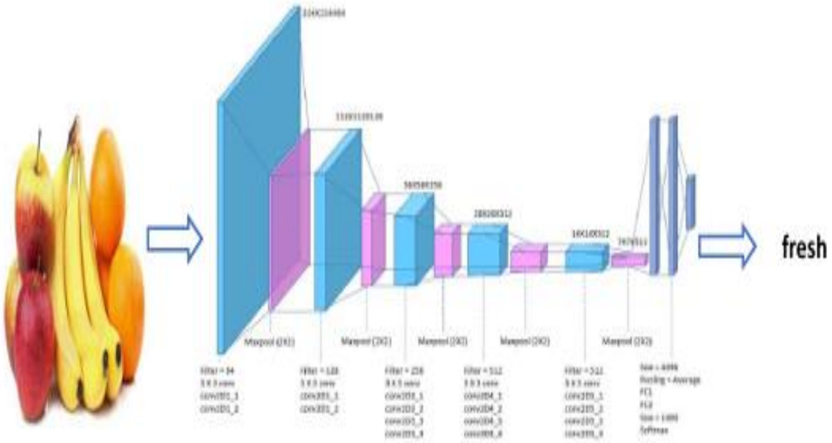

Fig 1: Proposed System Architecture

The model is trained using the Adam optimizer and categorical cross-entropy loss, with early stopping and model checkpointing applied to prevent overfitting. Performance is evaluated using accuracy metrics and loss curves across training, validation, and test datasets. This structured methodology effectively combines deep feature extraction, transfer learning, and optimized training strategies to build a reliable and accurate fruit detection system suitable for real-world applications.

4. Results and Discussion

Model accuracy is evaluated by analyzing the relationship between accuracy and the number of training epochs. An epoch refers to one complete cycle in which the neural network is trained using the entire training dataset exactly once. During each epoch, the model performs a forward pass to generate predictions and a backward pass to update the network weights. The following diagram illustrates how the model accuracy changes across epochs, providing insight into the learning behavior and performance improvement of the model over the training process.

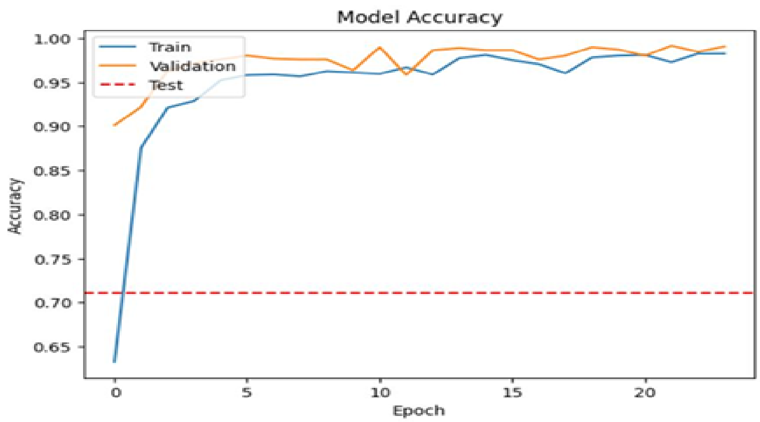

Fig 2: Model Accuracy Output

The Figure 2 illustrates a graph titled "Model Accuracy," which displays the model's performance over training epochs. The X-axis represents the number of epochs, or training cycles, while the Y-axis measures accuracy. There are three lines: a blue line showing training accuracy, an orange line representing validation accuracy, and a red dashed line indicating the test accuracy, which appears to be set at a threshold of 0.7. Both the training and validation accuracy curves rise sharply in the initial epochs, leveling off above 0.95, while the test accuracy stays constant at 0.71.

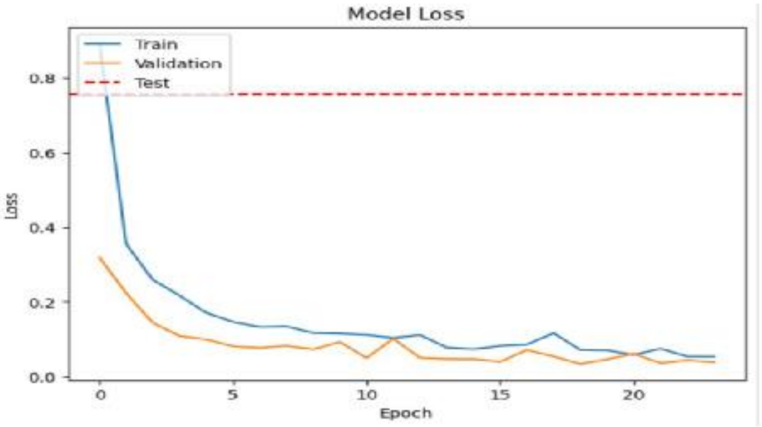

Fig 3: Model Loss Output

The graph shows the model loss over epochs for training, validation, and test datasets in the above Figure 3. The blue line represents the training loss, which decreases steadily, indicating that the model is learning. The orange line shows the validation loss, which also decreases and stabilizes, suggesting that the model generalizes well on unseen data. The red dashed 39 line represents the test loss, which remains high, possibly indicating a discrepancy between training/validation and test data, or that the test data is harder to predict.

Table 1: Analysis of the proposed model

Model	Accuracy (%) (1 Layer) on ImageNet
VGG19	71.6%
SqueezeNet	57.5%
ResNet18	69.8%

VGG19 achieves the highest accuracy at 71.6%, making it ideal for applications where accuracy is crucial and computational resources are available as shown in the above table 1. SqueezeNet, with its focus on efficiency and compact size, has the lowest accuracy at 57.5%, suitable for resource-constrained environments. ResNet18, offering a balance between accuracy (69.8%) and efficiency, benefits from residual connections to improve learning. VGG19 excels in performance but is more computationally intensive, while SqueezeNet is optimal for minimal resource usage. ResNet18 provides a middle ground, enhancing performance with efficient architecture.

5. Conclusion

The experimental results demonstrate that the VGG19-based transfer learning model achieves high accuracy in fruit detection, confirming its effectiveness in distinguishing between different types of fruits. The model's strong feature extraction capability makes it a reliable and powerful approach for image classification tasks, while the use of a pre-trained network provides a solid foundation with reduced training effort. Continuous evaluation and refinement can further enhance the model's adaptability and performance in real-world environments. Looking ahead, the application of transfer learning in fruit detection holds significant potential, with opportunities to explore more advanced deep learning architectures to improve accuracy and robustness. Integration with IoT-enabled systems can support real-time monitoring and automation in agriculture, promoting smarter farming practices. Moreover, the technology can be extended to applications such as augmented reality, personalized nutrition analysis, and food safety, thereby expanding its usefulness across multiple domains and industries.

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