IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Fruit Classification Using Transfer Learning

Akash.P.P[1], Nagendran.R[2], Aswin.R[3], Bhuvaneshwaran.N[4]

[2] Professor, Department of CSE, Sri Ramakrisna Institute of Technology, Coimbatore, Tamil Nadu, India

[134]UG students, Department of CSE, Sri Ramakrisna Institute of Technology, Coimbatore, Tamil Nadu, India

Abstract- The classification of fruits is an essential task in agriculture, food processing, and retail industries, ensuring quality control and efficient sorting. Conventional methods depend on inspection, which is often slow, labor-intensive, and inconsistent. To address these limitations, this study employs Transfer Learning with pre-trained Convolutional Neural Network to develop an fruit classification system. In this research, deep learning models such as MobileNetV2 are fine-tuned to classify fruit images with high accuracy. The pre-trained networks are adapted to recognize different fruit categories by leveraging their feature extraction capabilities while significantly reducing training time. A Flask-based web application is developed to allow real-time classification, enabling user to upload fruit images and get instant predictions, making it ideal for real-time applications. The findings demonstrate that Transfer Learning is a highly effective approach for fruit classification, offering a scalable and reliable solution for automating the process. This system has potential applications in smart agriculture, automated food inspection, and digital marketplaces, enhancing efficiency and reducing human effort.

Keywords: Transfer Learning, Convolutional Neural Networks, , MobileNetV2, Flask, Smart Agriculture.

I. Introduction

The rapid growth in artificial intelligence (AI) have significantly transformed the field of computer vision, enabling the automation of tasks that traditionally required human expertise. One such application is fruit classification, which plays a crucial role in agriculture, food processing, and retail industries. Classification of fruits is essential for maintaining quality control, reducing waste, and optimizing supply chain operations. However, conventional methods, which primarily rely on manual inspection, are labor-intensive, and human error.

This study explains the use of Transfer Learning in Convolutional Neural Networks (CNNs) to develop a robust and efficient fruit classification system. Transfer Learning uses deep learning models and to get leverage knowledge from large datasets, significantly reducing training time while improving accuracy. This approach eliminates the need to train a CNN from scratch, making it highly effective for real-world applications.

In this research, MobileNetV2 is utilized to classify different fruit types based on their visual features. The trained models are tuned on a specialized fruit dataset to enhance their classification results. A Flask-based web application is developed, allowing user to upload fruit images and get instant results. Furthermore, ensuring seamless cloud-based access and scalability.

This study is to evaluate the effectiveness of transfer Learning in fruit classification and identify the most suitable model for real-time applications. Through extensive experimentation, results demonstrate that MobileNetV2 gives the best results, so that we can move for deployment in resource-constrained environments. The proposed system provides a scalable, high-accuracy, and real-time solution for automated fruit classification, with potential applications in smart agriculture, automated food inspection, and e-commerce.

II. Related Works

A. Verma et al. (2023) introduced a MobileNetV2-based model for fruit freshness classification, achieving 94.7% accuracy with optimized performance on edge devices [6]. Their approach is highly efficient, making it suitable for integration in automated systems like sorting machines. A. Mehta et al. (2023) also used MobileNetV2 for fruit classification in agricultural settings, but with an additional focus on quality assessment for fruits [7]. Both systems use deep learning and transfer learning to accurately classify fresh fruits and predict their quality. These models excel in operational environments with constrained computational power and are particularly effective for automation in agricultural sorting. However, they require fine-tuning for performance on multi-fruit classification tasks, and accuracy may decrease with fruits that exhibit overlapping or occluded features.

T. Singh et al. (2023) developed a system using InceptionV3 to classify local fruits, offering an accurate, low-latency solution for mobile applications [4]. This model demonstrated strong results in classifying regional fruits in environments where mobile hardware is used. K. Das et al. (2023) similarly used deep learning to develop a web-based fruit classification system, focusing on local varieties of fruits in India and achieving over 93.1% accuracy [5].

Both systems for local fruit types, making them ideal for specific regions. However, the models are limited in scalability, with difficulty in classifying fruits from other regions or new, unseen classes.

A. Bhatt and M. Joshi (2024) proposed a framework using transfer learning to improve classification of fruits with similar color and texture, such as apples and guavas, reaching 94.8% accuracy [1]. This approach uses data augmentation to increase diversity in training, particularly useful for distinguishing visually similar fruits. N. Darapaneni et al. (2022) focused on the classification of bananas, including sub-varieties, using CNNs and transfer learning, and achieved high accuracy in detecting fruit quality [14].These systems excel in niche applications where fruit varieties have minor visual differences and require high precision. However, both approaches lack generalizability to broader fruit categories and need large, region-specific datasets to maintain high performance.

J. A. James et al. (2024) proposed a few-shot learning model that leverages transfer learning for fruit segmentation tasks, reducing the need for large labelled datasets [16]. This model is capable of performing well with limited data, achieving promising results in fruit classification and segmentation. J. Nelson (2020) also applied MobileNetV2 for fruit classification, optimizing the model for mobile deployment [9]. His solution focuses on real-time fruit classification with low latency, making it a viable option for mobile devices in field applications. Both systems are designed for real-time applications and require minimal labeled data, making them suitable for mobile or remote use. However, few-shot learning requires frequent fine-tuning for better accuracy, and MobileNetV2 faces challenges when handling high-resolution or cluttered fruit images.

M. Patel et al. (2024) developed XAI-Fruit Net, an explainable AI model for fruit classification that uses ResNet and Grad-CAM to give good results of deep learning models [2]. This model achieves over 96% accuracy in classifying various fruits and provides trustworthiness of AI-based fruit classification systems. This makes user to understand why certain fruits were classified in a specific way. S. Kumar et al. (2023) further advanced fruit classification by integrating feature fusion with deep learning, combining handcrafted and deep features to improve classification accuracy in cluttered and complex environments [3]. The method reaches high accuracy in distinguishing fruits in environments with varying lighting and background clutter. Both methods show excellent performance in classifying fruits under ideal conditions and have a high level of interpretability. However, they struggle in real-time processing environments due to increased computational requirements.

III. DATASET COLLECTION AND PREPROCESSING

The dataset used in this fruit classification project comprises real-world images categorized into three fruit types- apples, bananas, and oranges with each further classified based on quality as fresh or rotten. Each category contains over 400 images, organized into folders corresponding to their class labels. For preprocessing, all images are resized to 100x100 pixels and normalized to a scale of 0 to 1 using TensorFlow's Image Data Generator. The same tool also applies data augmentation techniques such as rotation, zooming, and flipping to improve model . A validation split is included to evaluate model performance during training.

TABLE I. DETAILS OF TRAINING, VALIDATION IMAGES USED

Dataset	Total	Total fresh fruits	Total rotten fruits	Training	Validation
apples	142	254	149	80%	20%
bananas	147	254	149	80%	20%
oranges	147	254	149	80%	20%

IV. PROPOSED METHODOLOGY AND METHODS

The proposed Fruit Classification Using Transfer Learning system follows a structured workflow to ensure accurate and efficient fruit classification. The process begins with dataset collection and preprocessing, where fruit images are gathered from multiple sources and undergo enhancement techniques such as resizing (rotation, flipping, and brightness adjustments) to improve the model. Next, feature extraction and model selection take place using pre-trained CNN architectures like MobileNetV2. The model is fine-tuned on the fruit dataset, leveraging transfer learning to extract deep features without requiring extensive training from scratch.

Once features are extracted, the classification and training phase is executed. The final classification layer utilizes a Softmax activation function to categorize fruits into multiple classes. The model's performance is assessed using performance metrics to ensure reliability. After successful training, it is deployed as a web application using Flask, allowing user to upload fruit images and get results. This end-to-end automated system ensures scalability, accuracy, and accessibility, making fruit identification more efficient and practical for applications in agriculture, food industries, and quality control systems.

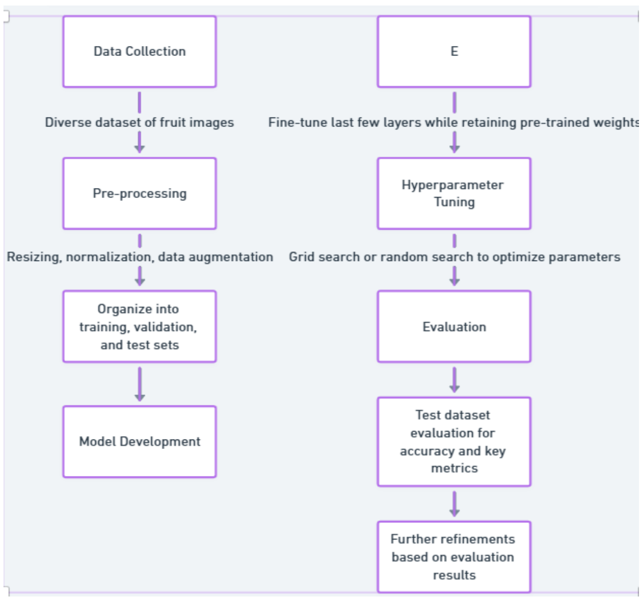

Fig.1 Methodology

Data Acquisition

A dataset of fruit images is collected from public sources or captured manually. Already trained deep learning model such as MobileNetV2 are utilized for feature extraction. Transfer learning enables the reuse of learned features, minimizing training time and improving accuracy.

Classification Model

The extracted features are moved using a fully connected layer for. A activation function is used to predict fruit category based on probabilities.

Model Training and Evaluation

The dataset is split into training and validation sets to ensure proper evaluation. Performance metrics are used to measure classification efficiency.

Deployment and User Interface

The trained model is deployed using Flask API or cloud-based platforms for real-time classification. A web-based or mobile application allows user to upload images and get results instantly.

V. Experimental Result and Discussion

This system is evaluated using a dataset consisting of real-world images of apples, bananas, and oranges, categorized further by quality as fresh or rotten. Approximately 400 images were used per class, and an 80:20 training-validation split was applied using TensorFlow's Image Data Generator. The model employed transfer learning with MobileNetV2 as the base architecture. Evaluation metrics were computed based on predictions made on unseen test images uploaded via a live Flask interface.

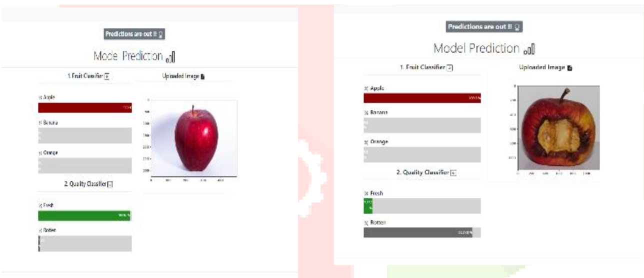

Fig.2 Testing Real-Time Results

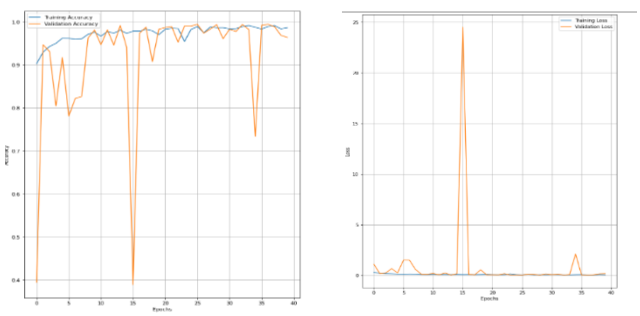

Fig.3 Training and Validation Graph

VI. Conclusion

The implementation of transfer learning for fruit classification has proven to be both efficient and practical in this project. By utilizing pre-trained convolutional neural networks such as MobileNetV2 and the system was able to effectively learn from a relatively small dataset, significantly reducing the time and computational resources required for training from scratch. The model accurately identifies the fruits and also distinguished their quality as fresh or rotten based on visual characteristics. The use of data augmentation and normalization techniques during preprocessing helped in enhancing model generalization, ensuring robust performance even when tested with real-world images. The project also demonstrated the feasibility of deploying such a system through a simple Flask-based web interface, helps user to upload image and get instant results.

These results for agricultural automation, particularly in tasks like fruit sorting, quality grading, and inventory management. It not only improves operational efficiency but also reduces human error in quality control processes. Overall, the project successfully meets its objectives and lays a strong foundation for further development in real-time fruit classification systems.

VII. REFERENCES

[1] **A. Bhatt and M. Joshi**, "Leveraging Deep Transfer Learning for Precision in Similar Color and Texture-Based Fruit Classification," *Int. J. Next-Gener. Comput.*, vol. 15, no. 3, 2024.

[2] **M. Patel et al.**, "XAI-FruitNet: An Explainable Deep Learning Model for Fruit Classification," *Sci. Direct*, 2024.

[3] **S. Kumar et al.**, "Fruit Type Classification Using Deep Learning and Feature Fusion," *ResearchGate*, 2023.

[4] **T. Singh et al.**, "Local Fruit Classification and Recognition Using Transfer Learning Models," *ResearchGate*, 2023.

[5] **K. Das et al.**, "A Deep CNN Approach to Detect and Classify Local Fruits Through a Web-Based System," *Sustainable Computing: Informatics and Systems*, vol. 15, no. 3, 2023.

[6] **A. Verma et al.**, "Automatic Fruits Freshness Classification Using CNN and Transfer Learning," *Appl. Sci.*, vol. 13, no. 14, p. 8087, 2023.

[7] **A. Mehta et al.**, "Intelligent Fruit Quality Classification System Using Transfer Learning," *J. Agric. Inform.*, vol. 13, no. 1, 2023.

[8] **R. Pathak and H. Makwana**, "Classification of Fruits Using Convolutional Neural Network and Transfer Learning Models," *J. Manag. Inf. Decis. Sci.*, vol. 24, Special Issue 3, 2021.

[9] **J. Nelson**, "Transfer Learning with Fruit Classification," *Towards Data Science*, 2020.

[10] **M. W. Tahir et al.**, "Transfer Learning for Classification of Fruit Ripeness Using VGG16," *Proc. Int. Conf. Comput. Sci. Inf. Technol.*, 2019.

[11] **S. Palakodati et al.**, "Fresh and Rotten Fruits Classification Using CNN and Transfer Learning," *ResearchGate*, 2020.

[12] **A. Sukkasem and C. Jitsakul**, "Fruit Classification with Deep Transfer Learning Using Image Augmentation," *Proc. Int. Conf. Comput. Sci. Inf. Technol.*, 2019.

[13] **M. W. Tahir et al.**, "Effectiveness of Transfer Learning and Fine Tuning in Automated Fruit Classification," *Proc. Int. Conf. Comput. Sci. Inf. Technol.*, 2019.

[14] **N. Darapaneni et al.**, "Banana Sub-Family Classification and Quality Prediction Using Computer Vision," *arXiv preprint arXiv:2204.02581*, 2022.

[15] **J. J. Bird et al.**, "Fruit Quality and Defect Image Classification with Conditional GAN Data Augmentation," *arXiv preprint arXiv:2104.05647*, 2021.

[16] **J. A. James et al.**, "Few-Shot Fruit Segmentation via Transfer Learning," *arXiv preprint arXiv:2405.02556*, 2024.

[17] **M. W. Tahir et al.**, "A Fungus Spores Dataset for Machine Learning Applications," *IEEE Int. Conf. Control Syst. Comput. Eng. (ICCSCE)*, pp. 242–246, 2018.

[18] **M. W. Tahir et al.**, "A Fungus Spores Dataset for Machine Learning Applications," *IEEE Int. Conf. Control Syst. Comput. Eng. (ICCSCE)*, pp. 242–246, 2018.

[19] **M. W. Tahir et al.**, "A Fungus Spores Dataset for Machine Learning Applications," *IEEE Int. Conf. Control Syst. Comput. Eng. (ICCSCE)*, pp. 242–246, 2018.

[20] **M. W. Tahir et al.**, "A Fungus Spores Dataset for Machine Learning Applications," *IEEE Int. Conf. Control Syst. Comput. Eng. (ICCSCE)*, pp. 242–246, 2018.