EXPLORING DEEP LEARNING MODELS FOR IMAGE RECOGNITION: A COMPARATIVE REVIEW

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ABSTRACT

Image recognition, which comes under Artificial Intelligence (AI) is a critical aspect of computer vision, enabling computers or other computing devices to identify and categorize objects within images. Among numerous fields of life, food processing is an important area, in which image processing plays a vital role, both for producers and consumers. This study focuses on the binary classification of strawberries, where images are sorted into one of two categories. We Utilized a dataset of strawberry images for this study; we aim to determine the effectiveness of different models in identifying whether an image contains strawberries. This research has practical applications in fields such as agriculture and quality control. We compared various popular deep learning models, including MobileNetV2, Convolutional Neural Networks (CNN), and DenseNet121, for binary classification of strawberry images. The accuracy achieved by MobileNetV2 is 96.7%, CNN is 99.8%, and DenseNet121 is 93.6%. Through rigorous testing and analysis, our results demonstrate that CNN outperforms the other models in this task. In the future, the deep learning models can be evaluated on a richer and larger number of images (datasets) for better/improved results.

KEYWORDS

Image recognition, Deep Learning, CNN, MobileNetV2, DenseNet121, Binary Classification, Strawberry Images

1. INTRODUCTION

Computer vision is a sub branch of Artificial Intelligence (AI). In computer vision, image processing techniques, such as detection and recognition have gained the utmost importance in different fields of life, such as food industries, and health-related image processing, to name a few. It includes the automatic categorization of objects within digital images [1, 2]. This technology has made considerable advancements in recent years, driven by improvements in Machine Learning (ML) and Deep Learning (DL) algorithms. These advancements have extended the application spectrum of image detection and recognition, spanning areas such as agriculture, food processing, autonomous driving, healthcare, and security [3, 4]. The importance of accurate image detection and recognition systems cannot be ignored, particularly in sectors where precision is critical [5, 6].

In a Binary classification, a learning technique, the tasks are fundamental yet challenging, requiring models to distinguish between two classes with good accuracy [7]. Several studies are available in this connection. For instant, in a study [8], the authors collected a dataset of 11,500 samples from Mendeley and employed various transfer learning models, including VGG16[1] and

[1] https://www.kaggle.com/code/blurredmachine/vggnet-16-architecture-a-complete-guide

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ResNet50[2]. Moreover, they presented a hybrid model, VGG16-ResNet that leverages the advantages of both architectures. By mixing multiple deep learning techniques and transfer learning strategies, such as VGG16-ResNet50, they developed a robust model capable of accurately classifying various ranges of dry foods. The approach in this study yielded good results, achieving a classification accuracy of 99.78% for numerous dry food images, even with partial training data for the VGG16-ResNet50 model.

Similarly, Y. Kim, *et al.*, *2024* [9], focus on integrated solutions by utilizing computer vision and deep learning (DL) technologies for ensuring the quality control and optimization of food processing in complex/hazardous environments. They used the Coffee Bean Classification Model (CBCM), developed using ML, and demonstrated good performance. It accurately distinguished coffee beans by navigating around obstacles. The CBCM achieved a maximum validation accuracy of 98.44% and a minimum validation loss of 5.40% after the 5^{th} epoch. After tested on a dataset of 137 samples, the CBCM attained an accuracy of 99.27% and a loss of 2.82%.

In a study on tomatoes [10], introduces a novel approach for tomato quality categorization and grading, leveraging pre-trained convolutional neural networks (CNNs) for feature extraction and traditional machine learning algorithms for classification in a hybrid model. Among the proposed hybrid models, the Convolutional Neural Networks- Support Vector Machine (CNN-SVM) method outperformed other hybrid approaches, achieving an accuracy of 97.50% in the binary classification of tomatoes as healthy or rejected and 96.67% in the multiclass classification of them as ripe, unripe, or rejected when InceptionV3 was used as the feature extractor.

Among delicate fruits, such as tomatoes and Strawberries are a significant crop in different regions of the world and are considered as most fragile. From 2017 to 2019, Florida's strawberry-planted area was second only to California, accounting for 20% of the total strawberry-planted area in the United States (US). Strawberry yield prediction is crucial for farmers, as it enables improved management of yield logistics, appropriate harvesting decisions, suitable labor hiring, and profit estimation [11]. Short-term strawberry yields can be accurately predicted by identifying and estimating the number of strawberries at different maturity stages [12].

To precisely classify the strawberry fruits based on advanced deep learning models, we need to compare the results generated by numerous deep learning models. This may help the partitioners to identify the raw and mature strawberry fruits accurately. We employed and compared several state-of-the-art deep learning models, including MobileNetV2, Convolutional Neural Networks (CNN), and DenseNet121, for the binary classification of strawberry images. MobileNetV2 is a well-known model for its efficiency and effectiveness in mobile and embedded vision applications [13]. CNNs have been the backbone of many image recognition breakthroughs due to their robust architecture for learning spatial hierarchies in images [14]. DenseNet121, with its tightly connected convolutional layers, promises efficient parameter usage and mitigation of the vanishing-gradient problem [15]. These models are chosen for their diverse architectures and proven performance in various image classification tasks.

This study focuses on a specific aspect of image recognition known as binary classification, which simplifies the categorization task by sorting images into one of two distinct groups. This study utilizes a dataset of strawberry images to explore the efficacy of various deep-learning models in correctly identifying whether an image contains strawberries. The practical applications of this research are significant, particularly in food processing, and agriculture, where automated systems for fruit detection can enhance efficiency and accuracy in processes like collecting and quality control [16]. The ability to accurately classify images as containing

[2] https://keras.io/api/applications/resnet/

strawberries or not can reduce labor costs and improve the consistency of agricultural outputs.

Through rigorous testing and analysis, our study reveals that the CNN model significantly outperforms MobileNetV2 and DenseNet121 in the task of binary classification of strawberry images. The accuracy achieved by MobileNetV2 was 96.7%, DenseNet121 scored 93.6%, and CNN reached an impressive 99.8%. These results underscore the superiority of CNNs in this specific context, highlighting their potential for deployment in real-world agricultural applications [17]. This paper aims to provide a detailed comparative analysis of these models, contributing valuable insights for practitioners seeking to implement deep learning solutions for image recognition tasks in various industries.

The rest of the paper is structured as follows: The Literature Review discusses a detailed yet comprehensive relevant literature. The Methods and Materials discusses the procedure carried out for this study. Results and Analysis depicted the results. The Conclusion part concludes the paper. The References are enlisted/enumerated at the end.

2. LITERATURE REVIEW

The precise detection and classification of various fruit species, and food in general, has become increasingly important [18, 19]. This area holds significant relevance not only in academic research but also in industrial applications. Many practical applications can be developed based on such classification systems. One prominent application involves its use in supermarkets to assist cashiers. Cashiers must accurately identify both the species and variety of fruits purchased by customers to determine the correct pricing. The pricing information must be stored in a query table. A classification-based application can automatically identify the fruit species purchased by the customer and match it with the correct price. This issue has been effectively addressed through barcode reader systems for packaged products. However, this solution does not apply to fruits and vegetables because customers typically select each piece of fruit individually when shopping in supermarkets.

The fruit classification system can also be implemented as a smartphone application. Numerous commercial and free applications (apps in short) are available in the market [20, 21]. These applications may assist individuals, particularly those with health concerns, in determining whether a specific fruit or vegetable meets their dietary needs. The application will identify the fruit species and present its corresponding nutritional information, essential details, and recommendations.

Unfortunately, fruit classification based on computer vision presents significant challenges due to:

- Resemblances in shape, color, and texture.
- Considerable differences within a single fruit category.

Numerous systems discussed in the literature aim to automate fruit inspection for defects, identify maturity stages, and recognize categories. For instance, a survey on fruit ripeness is discussed in [22]. Similarly, S. Marimuthu *et al*, [23] introduces a fuzzy model for classifying pineapple ripeness levels. This model extracts features such as peak hue and normalized brown area from the hue channel. Parameter tuning using Particle Swarm Optimization (PSO) yielded an accuracy of 93.11% on the MUSA database [24], comprising 3108 pineapple images at various ripening stages. Additionally, the same optimization technique was employed to parallelize computing resources for faster responses in a study [25].

Y. Zhang et al., [26] explored multi-class Kernel SVMs with appearance descriptors for fruit classification, achieving an accuracy of 88.2% on a dataset of 18 classes with 1653 color images using a combination of color, texture, and shape descriptors. Similarly, a hybrid classification approach proposed in [27], feedforward neural network classifiers trained via fitness-scaled chaotic artificial bee colony optimization achieved an accuracy of 89.1% on the same dataset, incorporating color histogram, texture, and shape descriptors.

Table 1: Relevant studies

Title	**Year**	**Key Contributions**	**Methods/Techniques Used**
[12]	2019	Introduced a novel deep learning-based method for classifying strawberry diseases with enhanced accuracy, leveraging cloud services for processing and analysis.	Improved residual networks, cloud services, data augmentation, image preprocessing, transfer learning
[28]	2021	Developed a system for automatic disease recognition in crops using CNNs, achieving high accuracy across multiple crop species and diseases.	Convolutional Neural Networks (CNNs), transfer learning, image augmentation, training on large datasets
[29]	2022	Proposed a self-supervised multi-network fusion model for detecting strawberry diseases, improving classification performance through network fusion techniques.	Self-supervised learning, multi-network fusion, transfer learning, data augmentation, deep learning models including CNNs and residual networks, hybrid model fusion

3. METHODS AND MATERIAL

This study focuses on a specific type of image recognition called binary classification. This means we want to sort images into one of two groups. For our experiment, we use a dataset of strawberry[3] images to see how well different models can tell if an image contains strawberries or not. Comparing several popular models, we aim to find out which ones work best for identifying strawberries. This can be very useful in areas like farming and quality control. Through careful testing and analysis of results, we will highlight which models are most effective for this task. We used MobileNetV2 for the Binary Classification of Strawberry Images, Convolutional Neural Network (CNN) for the Binary Classification of Strawberry Images, and DenseNet121 for the Binary Classification of Strawberry Images. All these algorithms are compared. Results show that CNN outperforms other algorithms. Figure 1 show the workflow of machine and deep learning models.

[3] https://www.kaggle.com/datasets/abdulbasit31/strawberry-dataset/data

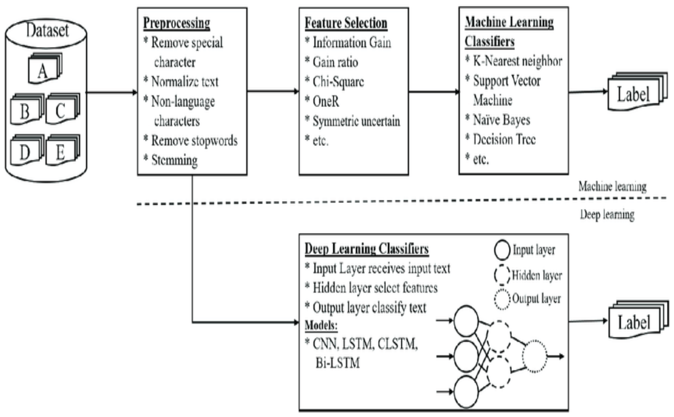

Figure 1: Workflow of machine and deep learning models [30]

4. Results and Analysis

In this section, the results are analyzed. The three algorithms are evaluated based on a single dataset. The following sub-section demonstrated the results as:

5. MobileNetV2 for Binary Classification of Strawberry Images

The MobileNetV2 model is initialized with pre-trained weights from the ImageNet dataset and adapted for binary classification by removing the top layers responsible for classifying ImageNet categories.

Introduction to MobileNetV2: MobileNetV2 is a lightweight convolutional neural network architecture designed for efficient image classification tasks, particularly suited for deployment on mobile and embedded devices. Its architecture consists of depth-wise separable convolutions and inverted residual blocks, allowing for effective feature extraction while minimizing computational resources. In this study, we employ MobileNetV2 as a feature extractor for the binary classification of strawberry images.

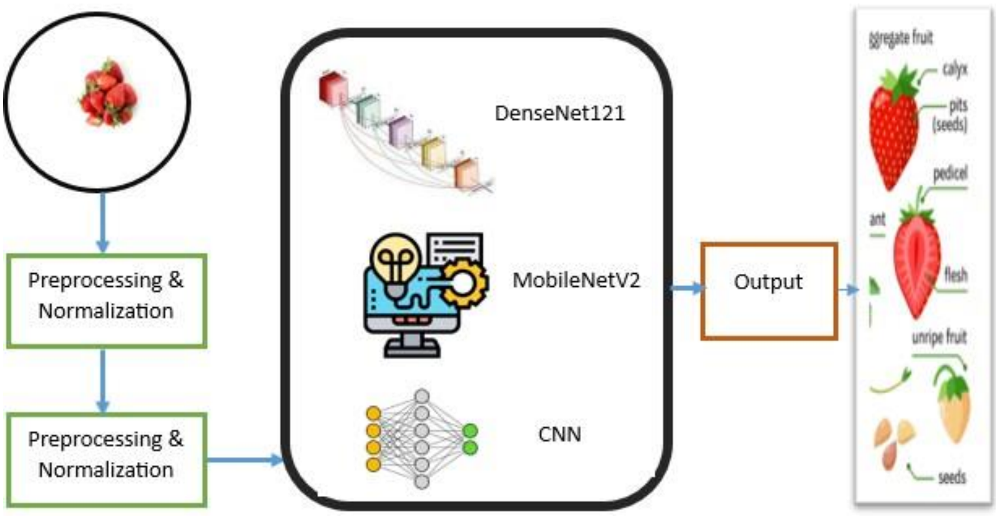

Fig 2: The schematic diagram of the proposed solution.

A custom classification layer is added on top of the base MobileNetV2 architecture to classify images as either containing pickable or unpickable strawberries. During training, the base MobileNetV2 layers are frozen to retain learned features, while only the classification layer is trained on the strawberry dataset. This transfer learning approach enables the model to quickly adapt to the new task with relatively few training examples.

Results and Performance Evaluation: Training the MobileNetV2 model on a dataset of strawberry images results in impressive performance metrics. After 20 epochs of training with data augmentation techniques applied to increase robustness, the model achieves a training accuracy of approximately 96.7% and a training loss of 0.193. The validation accuracy is around 80.6%, with a validation loss of 0.400. Precision, recall, and F1-score metrics are calculated for both classes, showing the model's ability to effectively distinguish between pickable and unpickable strawberries. The confusion matrix visualizes the model's predictions compared to the true labels, revealing few misclassifications and overall strong performance.

6. Convolutional Neural Network (CNN) for Binary Classification of Strawberry Images

Introduction: In this study, a custom Convolutional Neural Network (CNN) is employed for binary classification of strawberry images. CNNs are particularly well-suited for image recognition tasks due to their ability to automatically learn spatial hierarchies of features through convolutional layers. The objective is to classify images into two categories: "Pickable" (images containing pickable strawberries) and "UnPickable" (images without pickable strawberries). The CNN model is designed with several layers to effectively capture and learn features from the strawberry images:

Table 2: CNN model structure

Input Layer:	A Conv2D layer with 32 filters of size 3x3 and ReLU activation function processes the input images of size 224x224x3.
Convolutional Blocks:	The model includes multiple convolutional blocks with increasing filter sizes (64 and 128) and ReLU activation functions. Each block consists of a Conv2D layer followed by Batch Normalization, MaxPooling2D for down-sampling, and Dropout to prevent overfitting.
Flatten Layer:	The Flatten layer converts the 2D feature maps into a 1D feature vector.
Fully Connected Layers:	A Dense layer with 512 units and ReLU activation is added, followed by a Dropout layer.
Output Layer:	A Dense layer with a single unit and sigmoid activation function provides the binary classification output.
Training Strategy:	The model is trained using the Adam optimizer with a learning rate of 0.0001 and binary cross-entropy loss.

The data augmentation techniques such as rotation, shifting, shearing, zooming, and horizontal flipping are applied to the training set to improve generalization. The dataset is split into 80% training and 20% validation subsets using Image Data Generator. The results show that Training Loss is about 0.062, where training accuracy is 99.8%. The validation loss was around 1.196 whereas the validation accuracy is 96.1%.

7. DENSENET121 FOR BINARY CLASSIFICATION OF STRAWBERRY IMAGES

Introduction: DenseNet121 is a state-of-the-art convolutional neural network (CNN) architecture designed to facilitate efficient feature reuse through dense connectivity between layers. This model is particularly effective for image classification tasks due to its ability to capture intricate details and hierarchical features. The DenseNet121 is employed for the binary classification of strawberry images, distinguishing between "Pickable" and "UnPickable" categories.

Table 3:DenseNet121 model structure

Model Structure	The DenseNet121 model is adapted for this binary classification task by leveraging transfer learning
Base Model:	The DenseNet121 model is initialized with pre-trained weights from the ImageNet dataset. The top layers of DenseNet121, which are responsible for classifying ImageNet categories, are excluded.
Custom Layers:	A GlobalAveragePooling2D layer is added to reduce the dimensionality of the feature maps output by DenseNet121. A Dense layer with a single unit and sigmoid activation function is used to perform binary classification.
Freezing Base Layers:	The base layers of DenseNet121 are frozen during training to preserve the learned features from ImageNet, which helps in achieving faster convergence and better generalization with limited training data.
Data Augmentation:	The training data is augmented using techniques like rotation, width and height shifts, shearing, zooming, and horizontal flipping to enhance the model's robustness.

The dataset is split into 80% training and 20% validation subsets using Image Data Generator. The model is compiled with the Adam optimizer (learning rate: 0.0001) and binary cross-entropy loss. The model is trained for 20 epochs. We achieved a training accuracy: of 93.6% at the loss of training Loss: 0.369. Similarly, validation accuracy was 83.5% with a validation loss of 0.423.

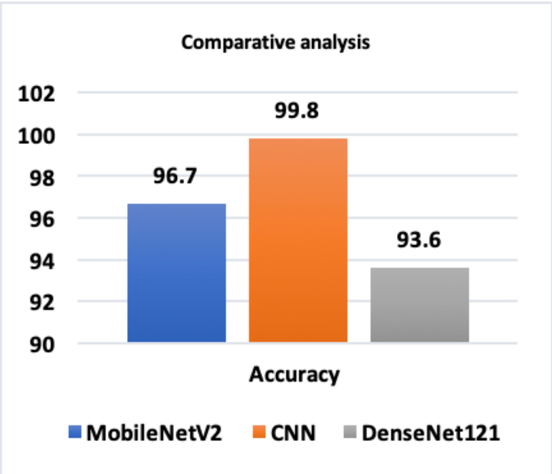

Fig 2. Comparative analysis of models based on accuracy

Figure 2 shows a comparative analysis of all three models evaluated in this study. Results show that CNN outperforms the rest of the models. Results may be different on other datasets and approaches.

8. CHALLENGES

A few challenges are still necessary to explain like the limited size datasets for such classification. The deep learning algorithms are data-hungry for accurate dictation and classification [31]. Moreover, the classification of fruits such as strawberries, and apples is easy to detect due to their colors and similarities in features; however, more entropy in data may lead to inaccurate results [32]. Furthermore, the model may perform well in controlled environments, such as theoretically, however, its transferability to real-world scenarios with varying lighting conditions, and diverse backgrounds needs to be validated. Ensuring the model's robustness across different real-world conditions is essential for practical deployment.

9. FUTURE WORK

The evaluation of the models on a richer and larger dataset that includes more images captured under various conditions, such as different lighting, angles, and backgrounds may improve generalizability and robustness. Extending the research to multi-class classification, instead of binary classification, where the model not only identifies the presence of strawberries but also distinguishes between different types of fruits or diverse quality grades of strawberries. Moreover, utilizing transfer learning to adapt models pre-trained on large datasets to the task of strawberry classification, could improve performance. Furthermore, using ensemble methods to combine the strengths of multiple models, such as MobileNetV2, CNN, and DenseNet121, to achieve improved performance and consistency. The integration of image data with other types of sensor data (e.g., high pixel camera, temperature, humidity may improve the accuracy and robustness of the classification models. Tailoring these models and solutions for specific agricultural applications, such as automated sorting and grading systems to address particular needs and challenges in the fields are some possible future works.

10. CONCLUSION

In conclusion, image recognition is pivotal in computer vision, allowing computers to identify and categorize objects within images. This study focused on the binary classification of strawberry images, assessing the effectiveness of various models in determining the presence of strawberries. The research holds significant practical applications in agriculture and quality control. For this classification task, we evaluated several prominent models, including MobileNetV2, Convolutional Neural Networks (CNN), and DenseNet121. The results revealed that MobileNetV2 achieved an accuracy of 96.7%, DenseNet121 attained 93.6%, and CNN excelled with an impressive accuracy of 99.8%. Through rigorous testing and analysis, it is evident that CNN outperforms the other models, establishing its superiority in the binary classification of strawberry images. The model can be used for many other similar fruits and vegetables, such as tomatoes, apples, oranges, to name a few. Moreover, this type of model can be used for quality control and sorting of various fruits/vegetables in food processing plants. This may help guarantee reliable quality products and reduce waste.

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