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Deep Learning-Based Classification of Melinjo Chips: Comparative Evaluation of CNN Architectures

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ABSTRACT

This study investigates the application of deep learning for automated classification of melinjo chips into three quality categories: super, small broken, and large broken. An initial hyperparameter optimization established a performance baseline, with the Adam optimizer (learning rate 0.0005), batch size of 32, and 100 epochs yielding 94.2% accuracy and an F1-score of 0.915. Subsequently, four pretrained Convolutional Neural Networks (CNNs)—ResNet50, ResNet18, MobileNetV2, and AlexNet—were assessed using standard metrics and confusion matrices. ResNet50 achieved the highest performance (accuracy 0.991, F1-score 0.985), demonstrating strong feature extraction capabilities. ResNet18 offered comparable results with shorter training time, while MobileNetV2 provided a favorable trade-off between computational efficiency and accuracy. AlexNet exhibited the lowest performance due to its shallow architecture. Real-time experiments indicated that higher accuracy often comes at the expense of inference speed: ResNet50 delivered superior discriminative metrics (area under the receiver operating characteristic curve (AUC) 0.961, average precision (AP) 0.962) but slower predictions, whereas MobileNetV2 enabled faster inference with slightly reduced precision. These findings emphasize the importance of balancing accuracy and efficiency for deploying deep learning models in food quality assessment systems.

1. INTRODUCTION

Snack chips are a popular snack choice among consumers, and their classification can be crucial for market segmentation and product development. The Central Statistics Agency (BPS) of Indonesia noted that the exports of crackers and chips reached US 37.77 million in 2023. The value increased by 1.35% compared to the previous year [1]. As the demand for diverse snack options continues to rise, understanding the nuances of consumer preferences becomes essential for manufacturers aiming to enhance their product offerings.

Figure 1. Melinjo fruit (left) and melinjo chips (right)

Melinjo chips, known as "emping melinjo", are a popular snack in Indonesia made from the mature seeds of the melinjo fruit (*Gnetum gnemon* plant). The process begins with the selection of mature melinjo seeds, which are then roasted. Roasting is a crucial step as it softens the seeds, making them easier to flatten. After roasting, the seeds are flattened using a heavy object, typically a wooden pestle, to create thin discs [2]. These discs are then dried in the sun until they become crisp, resulting in a crunchy texture that is highly sought after (Figure 1). The flattening process can lead to inconsistent texture and shape in melinjo chips due to variations in pressure applied, resulting in uneven thickness. This inconsistency can affect the cooking and crisping of the chips, potentially leading to a less desirable texture. To mitigate these issues, some producers have begun to experiment with mechanical flattening methods that promise more uniformity in thickness and texture, thereby enhancing the overall quality of the final product.

The increasing variety of flavours and textures has led to a need for effective classification methods that can accurately categorize these products based on consumer preferences and quality [3, 4]. As consumer preferences evolve, the ability to accurately classify these products becomes paramount for effective market segmentation and informed product development [5]. It is essential to develop highly accurate, reliable classification systems that can adapt to changing trends and preferences, ensuring that manufacturers stay ahead in a competitive landscape. Different methods, such as both traditional and modern methods, have been put forward to classify these products, including machine learning approaches, clustering methods, artificial intelligence, and deep learning [6]. The key differences between traditional and modern methods of product classification lie in their approach, efficiency, and adaptability to complex data. Traditional methods often rely on feature extraction and predefined rules for product classification, which can limit their adaptability to complex textual data [7], while modern methods leverage advanced technologies such as machine learning and deep learning to automate and enhance the classification process [8].

Food classification is a critical task in computer vision with applications in nutrition monitoring, food safety, and smart agriculture. Traditional machine learning approaches required manual feature engineering, which limited scalability and generalization. In contrast, deep learning architectures such as Convolutional Neural Networks (CNNs) have revolutionized food classification by enabling end-to-end learning directly from raw images [9]. Over the past decade, models like ResNet, MobileNet, and EfficientNet have been widely adopted to classify food items with high accuracy across diverse datasets.

Recent studies highlight the role of deep learning in food recognition for dietary assessment, food quality monitoring, and agricultural product classification. For example, Liu et al. [10] provided a comprehensive review of food image recognition using CNNs, while Chen et al. [11] demonstrated the effectiveness of MobileNetV2 in agricultural product classification. Qiu et al. [12] applied deep learning for automated food image classification in nutrition monitoring, and Nfor et al. [13] showed the potential of CNN-based approaches for food classification tasks. More recently, hybrid approaches combining CNNs and vision transformers have been explored for fine-grained food category classification, further improving accuracy and robustness [14].

These findings consistently demonstrate that deep learning not only surpasses classical methods but also supports real-time applications on mobile and embedded devices. As food systems become increasingly digitized, deep learning continues to provide a powerful framework for advancing intelligent food classification solutions.

Deep learning has emerged as a transformative technology in the food industry, particularly in the quality control and safety assessment of chips. These technologies enable more accurate detection of defects and anomalies, ensuring that only the highest quality products reach consumers. Deep learning models, particularly CNNs, have been effectively used to detect defects in potato chips. The SqueezeNet CNN architecture was used in a study to pull out features from pictures of potato chips. It was able to achieve high classification accuracy with Artificial Neural Networks (ANN), K Nearest Neighbor (KNN), and Random Forest (RF) [15]. Another study explored the use of ResNet50 and Inception-V3 models for defect detection in 3D food printing, which can be analogous to potato chip production, achieving accuracies of 93.83% and 84.62%, respectively [16]. Deep learning, specifically ANNs, has been applied to predict the thermo-physical properties of deep-fried plantains, which share similarities with potato chips. The ANN model accurately predicted properties such as specific heat and density, demonstrating its utility in optimizing frying processes without extensive experimental testing [17]. Deep learning's application extends beyond defect and compound detection to broader food safety and quality assessments. It has been used to classify food items as healthy or unhealthy with 90% accuracy, showcasing its potential in consumer health protection [18]. Deep learning and the Internet of Things (IoT) have been combined to find out more about the quality and safety of food. This is because deep learning is better at dealing with large datasets and complex patterns than traditional methods [19].

The exploration of deep learning models such as ResNet, MobileNet, and AlexNet has significantly advanced the field of food image recognition and classification. These models have been adapted and optimized for various applications, including food security, dietary monitoring, and agricultural productivity. ResNet50 has been integrated with vision transformers to enhance plant disease classification, demonstrating its adaptability and effectiveness in capturing both local and global image features [20]. Additionally, ResNet50 has been employed in food allergy detection, where it achieved a 95% accuracy rate, showcasing its potential in dietary management [21]. The research developed a digital image classification system to identify diseases in corn plants, achieving a high accuracy of 95.59% using the ResNet-50 architecture [22]. The ResNet18-based model has been optimized for indoor agriculture applications, such as predicting crop yields [23]. MobileNetV2 is favored for its efficiency and lightweight nature, making it suitable for applications with limited computational resources. It has been effectively used in plant disease diagnosis, achieving high accuracy and enabling faster and more accurate disease detection compared to traditional methods [24]. AlexNet has been used to classify sugarcane leaf diseases, with different activation functions like ReLU and LeakyReLU affecting the model's accuracy and computational efficiency [25]. Various CNN architectures were tested, including SqueezeNet, AlexNet, and ResNet models, to compare their classification performance [22, 26].

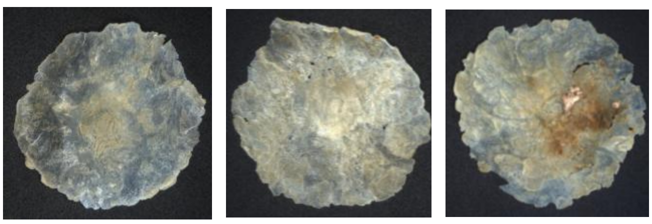
Even though CNNs have garnered significantly greater focus in comparison to alternative machine learning methodologies, their application in the study of snack chips, specifically melinjo, has been rarely investigated. Previous works on food classification have primarily concentrated on broader categories such as fruits, vegetables, or prepared meals, often utilizing architectures like ResNet, MobileNet, or Inception to achieve high accuracy [14, 27, 28]. However, studies targeting niche or region-specific food items remain limited, and critical challenges such as dataset variability, reproducibility, and generalization across diverse food types are still insufficiently addressed. The aim of this study is therefore to investigate the potential of CNNs in enhancing the classification of melinjo chips by applying different models and evaluating their performance.

2. MATERIALS AND METHOD

2.1 Dataset preparation

The dataset used in this study consists of images of melinjo chips collected from various production batches from melinjo chip producers in Pidie regency, Aceh, Indonesia, ensuring a diverse representation of quality and appearance. Three different types of melinjo chips were included: large broken, small broken, and super (Figure 2), each categorized based on their unique characteristics and processing methods. In total, 1,500 images were collected and subsequently divided into training (70%), validation (15%), and testing (15%) subsets. To prevent data leakage and ensure the reliability of the evaluation, images from a given production batch were allocated exclusively to either the training, validation, or testing set, but were not shared across multiple splits. This approach was adopted to ensure that the reported performance reflects the model's ability to generalize beyond batch-specific characteristics.

The images were taken using a CCD camera (DBK41BU02.H, The Imaging Source Europe GmbH, Bremen, Germany) equipped with a 4.5–12.5 mm lens (Computer H3Z4512CS-IR 1/2" varifocal day/night lens). Images were taken from multiple angles and distances to reflect realistic scenarios, and with controlled light conditions. The image acquisition was performed with the IC Capture version. 2.5 TIS software (The Imaging Source Europe GmbH, Bremen, Germany). The image was captured against a black background of a conveyor belt to construct the model, which will be subsequently employed to categorize other melinjo chip samples in real-time (see subsection 2.2). Data augmentation techniques were applied to improve model generalization and reduce overfitting, including rotations and brightness variation adjustment. All experiments were conducted on a laptop running Windows 11, equipped with an Intel Core i5 CPU (12th Gen Intel, 4.40 GHz), integrated Intel Iris Xe Graphics with 8 GB system RAM.



super small broken large broken

Figure 2. Classification of melinjo chips into three categories

Figure 3. Setting for real-time classification of melinjo chips

2.2 Real-time classification setting

Real-time classification was conducted for all classifiers (4 classifiers), with each classifier classifying 300 melinjo chips at a conveyor belt speed of 2 cm/s (Figure 3). In this study, real-time image acquisition was performed using the Iriun 4K webcam application, which enabled the smartphone camera to function as a webcam connected to the PC via USB. The images were taken using the Infinix Note 30, which has a 64 MP main rear camera (f/1.69 aperture) and supports video resolution of 1440p at 30 fps and 1080p at 30/60 fps options.

2.3 Convolutional Neural Network

For model training, the image dataset was pre-processed to a standardized square format of 224 × 224 pixels. Regularization was applied using a weight decay of 0.0001, and optimization employed a momentum value of 0.9. Four pretrained CNN classifiers, such as ResNet18, AlexNet, ResNet50, and MobileNetV2, were evaluated in this study. These models were customized and implemented using the MVTec Halcon software environment. The complete set of model parameters utilized in the experiments is presented in Table 1.

Table 1. Model parameters applied

Parameters	Objectives
Optimization algorithm	An optimization approach is employed during training to reduce the total loss function value.
Learning rate	The learning rate regulates the extent to which the model's weights are modified during training.
Batch size	The batch size specifies the quantity of images processed prior to an update of the model's weights.
Momentum	Momentum is used to smooth out gradient updates and accelerate convergence.
Weight decay	This regularization term mitigates excessive weight values, enhancing the model's generalization capacity and preventing overfitting.
Image size	To preserve consistency across the dataset and guarantee compatibility with deep learning frameworks.
Epochs	The number of epochs was chosen to provide adequate learning while avoiding overfitting.

2.3.1 ResNet18

ResNet18 (pretrained_dl_classifier_resnet18.hdl) is part of the ResNet family of residual networks that utilize skip connections to enhance the flow of information and gradients throughout the layers, allowing for more effective training on complex datasets. The architecture consists of 18 layers, which include convolutional layers, batch normalization, and ReLU activation functions, making it suitable for image classification tasks. The model's ability to learn hierarchical features from the input images contributes significantly to its performance, particularly in distinguishing subtle variations between classes [29, 30].

2.3.2 AlexNet

AlexNet (pretrained_dl_classifier_alexnet.hdl) classifier is a pioneering CNN that played a crucial role in popularizing deep learning for image recognition. With its eight layers, including five convolutional layers and three fully connected layers, AlexNet introduced techniques such as dropout and data augmentation to combat overfitting and improve generalization. Its architecture is designed to capture complex patterns in images, making it particularly effective for large-scale classification tasks. AlexNet is a well-established CNN architecture that has been widely used for various image classification tasks. It is particularly effective in scenarios where large datasets are available, as it can learn complex features from the data [31].

2.3.3 ResNet50

ResNet-50 (pretrained_dl_classifier_resnet50.hdl) has emerged as one of the most influential deep CNN architectures in computer vision research [32]. Its design, based on residual learning, effectively addresses the vanishing gradient problem and enables the training of very deep networks with improved accuracy. Over the past five years, ResNet-50 has been widely applied to agricultural applications [16, 20, 33, 34].

2.3.4 MobileNetV2

MobileNetV2 (pretrained_dl_classifier_mobilenetv2.hdl) is a CNN architecture that is lightweight and optimized for mobile and embedded vision applications. It is a successor to MobileNetV1 and was developed by Google researchers. It introduces linear bottlenecks and inverted residuals, which considerably reduce computational costs while maintaining high accuracy [35]. This design is particularly well-suited for real-time agricultural monitoring and smart farming systems, as it facilitates the efficient deployment of deep learning models on resource-constrained devices. MobileNetV2 has been extensively implemented in precision agriculture, crop disease detection, and product classification duties over the past five years [36-38]. It has become the preferred choice for edge-based agricultural applications due to its capacity to balance efficiency and accuracy, which are essential in sectors where energy efficiency and low latency are essential. MobileNetV2's adaptability is further emphasized in recent studies when it is combined with data augmentation and transfer learning, which further enhances its robustness in a variety of agricultural environments [11].

2.4 Fine-tuning

CNNs pretrained on large-scale datasets (specifically ResNet50, ResNet18, MobileNetV2, and AlexNet) were adapted to the task of melinjo chip classification by selectively unfreezing their final layers (Figure 4). To ensure reproducibility, the fine-tuning procedures applied to all pretrained models are detailed as follows. Two strategies were considered: a frozen backbone, where convolutional layers were kept fixed, and only the fully connected layers were retrained, and full fine-tuning, where all layers were optimized. Training followed a step-decay learning rate schedule, starting at 0.001 and reduced by a factor of 0.1 every ten epochs. Early stopping was implemented with a patience of ten epochs.

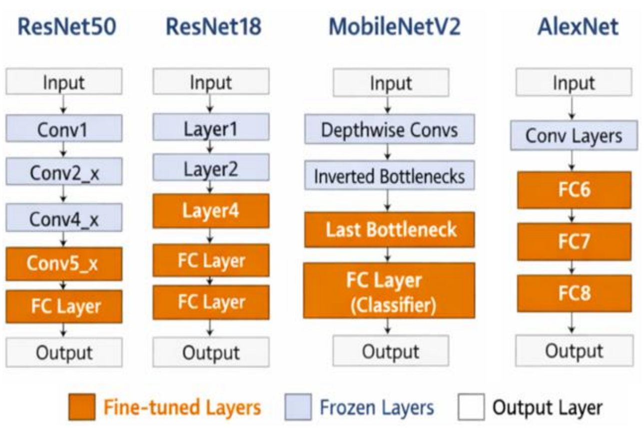


Figure 4. Models' architectures of fine-tuning

Note: The output layer is modified from the original 1000 ImageNet classes to three melinjo chip categories (super, small broken, large broken).

In the case of ResNet50 and ResNet18, the last residual block together with the fully connected layers were retrained; for MobileNetV2, the final bottleneck block and classifier were adjusted; and for AlexNet, the three fully connected layers (FC6, FC7, and FC8) were optimized. This targeted fine-tuning strategy enabled the networks to refine high-level feature representations in line with the characteristics of the melinjo dataset.

2.5 Evaluation matrix

Various evaluation metrics were employed to assess the performance of the classifiers (Eqs. (1)-(6)), including accuracy, precision, recall, and F1-score [11]. These metrics provide a comprehensive understanding of how well the models perform under different conditions and help identify areas for improvement. The formula of these metrics can be expressed in Table 2.

Table 2. Evaluation matrix formula

Formula	What it Measures	Equations
$Accuracy = \frac{TP+TN}{Total\ of\ data\ used}$	Overall correctness of the model	(1)
$Precision = \frac{TP}{TP+FP}$	Correctness of positive predictions	(2)
$Recall = \frac{TP}{TP+FN}$	Ability to find all positive instances	(3)
$F1-score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$	Harmonic mean of precision and recall	(4)
$True\ Positive\ Rate = \frac{TP}{TP+FN}$	Proportion of actual positives correctly identified	(5)
$False\ Positive\ Rate = \frac{FP}{FP+TN}$	Proportion of actual negatives incorrectly classified as positives	(6)

True Positive (TP) refers to positive samples that are correctly identified, while False Positive (FP) denotes negative samples that are mistakenly classified as positive. True Negative (TN) represents negative samples accurately recognized as such, and False Negative (FN) indicates positive samples that are incorrectly labeled as negative. These four quantities form the foundation for calculating key evaluation metrics, including accuracy, precision, recall, and the F1-score. They also support the construction of receiver operating characteristic (ROC) and precision-recall (PR) curves [39], which together provide a comprehensive view of classifier performance.

The area under the curves (AUC)-ROC is defined as the integral of the True Positive Rate with respect to the False Positive Rate, offering a measure of the classifier's overall discriminative ability. In contrast, the AUC-PR curve emphasizes the trade-off between precision and recall, making it particularly valuable for imbalanced datasets where positive samples are relatively rare. For finding AUC, the trapezoidal rule was used [40, 41].

2.6 Hyperparameter tuning and comparative evaluation

Hyperparameter tuning was carried out in a structured manner using the MVTec Halcon software. Several configurations were explored, including the choice of optimizer (Adam and stochastic gradient descent (SGD)), different learning rates (0.001, 0.0005, 0.0001), batch sizes (16, 32, 64), and varying numbers of epochs (50, 100, 150). Each setup was evaluated on the validation set through a grid search strategy, with performance measured in terms of accuracy, F1-score, and the standard deviation across multiple runs to ensure both convergence stability and generalization. To obtain reliable estimates of variability, every experiment was repeated five times, and the mean values together with their standard deviations were reported. The configuration that delivered the most consistent results was selected as the baseline for subsequent comparisons across classifier architectures.

In addition, four pretrained classifiers provided by the HALCON deep learning framework (AlexNet, ResNet18, ResNet50, and MobileNetV2) were tested under the same experimental settings to provide a comparative evaluation. Their outputs were analyzed using confusion matrices. Real-time classification experiments were also conducted for all four models. Overall accuracy and F1-score were computed to assess predictive reliability, while AUC-ROC and AUC-PR metrics were used to evaluate discriminative ability and threshold-dependent behavior. Furthermore, the inference time per sample was measured to capture computational efficiency during real-time processing.

3. RESULTS AND DISCUSSION

3.1 Hyperparameter and fine-tuning

The results of hyperparameter tuning establish a clear baseline for evaluating model performance before conducting comparative tests across different classifier architectures. The experiments produced accuracies ranging from 91.5% to 94.2%, with F1-scores between 0.874 and 0.915 (Table 3).

Among the tested settings, the configuration using the Adam optimizer with a learning rate of 0.0005, batch size of 32, and 100 training epochs yielded the most consistent outcomes, achieving 94.2% accuracy, an F1-score of 0.915, and the lowest variability (±0.5). This setup combined strong predictive capability with stable convergence on the importance of learning rate schedules [42] and the stability of training with moderate batch sizes [43]. In contrast, the use of SGD resulted in slightly lower accuracy and greater variance. Extreme learning rate values (0.001 or 0.0001) and smaller batch sizes also reduced stability. Likewise, shorter training runs (50 epochs) led to underfitting, while extending training to 150 epochs introduced minor overfitting without meaningful performance improvements [44].

Table 3. Hyperparameter tuning

Configuration	Accuracy (%) ± Standard Deviation	F1-Score
Optimizer Adam	92.0 ± 0.9	0.875
Optimizer Stochastic Gradient Descent (SGD)	91.5 ± 1.0	0.874
Learning rate 0.001	92.2 ± 0.8	0.880
Learning rate 0.0001	92.8 ± 0.9	0.890
Learning rate 0.0005	93.5 ± 0.7	0.900
Batch size 16	92.3 ± 0.8	0.885
Batch size 32	93.8 ± 0.6	0.905
Batch size 64	92.5 ± 0.9	0.890
Epochs 50	92.1 ± 0.8	0.880
Epochs 100	94.2 ± 0.5	0.915
Epochs 150	93.7 ± 0.6	0.910

Table 4. Accuracy and inference time of the model after fine-tuning

Model	Increasing Accuracy	Increasing Inference Time
ResNet50	+5.6%	+0.07 s
ResNet18	+4.6%	+0.03 s
MobileNetV2	+5.7%	+0.02 s
AlexNet	+3.2%	+0.02 s

The results of the fine-tuning led to consistent improvements in classification accuracy across all models (Table 4). ResNet50 and MobileNetV2 achieved the most substantial gains, with increases of 5.6% and 5.7%, respectively. ResNet18 also showed a notable improvement of 4.6%, while AlexNet recorded a smaller rise of 3.2%. These accuracy gains were accompanied by minor increases in inference time, ranging from 0.02 to 0.07 seconds. Overall, the findings underscore the trade-off introduced by fine-tuning: accuracy is enhanced considerably, while the additional computational cost remains minimal, thereby maintaining the practicality of real-time deployment, particularly for lightweight architectures such as MobileNetV2.

3.2 Classifier performance

A comparative study was undertaken on four CNN architectures (ResNet18, ResNet50, MobileNetV2, and AlexNet) to classify melinjo chips into three categories: super, small broken, and large broken (Figure 5).

The evaluation relied on confusion matrix visualization and standard performance metrics. ResNet50 emerged as the most reliable model, achieving a precision of 0.986, a recall of 0.986, an F1-score of 0.985, and an overall accuracy of 0.991 (Table 5). These results are consistent with recent work that highlighted the stability and generalization capacity of ResNet50 in structural image analysis tasks [45].

MobileNetV2 followed with an accuracy of 0.980 and an F1-score of 0.970 (Table 5). Despite its lightweight design, the model demonstrated strong performance, confirming the efficiency-accuracy balance reported in studies of resource-constrained environments. The diagonal dominance observed in its confusion matrix further supports its robustness in fine-grained classification; a finding echoed in biomedical imaging applications [46].

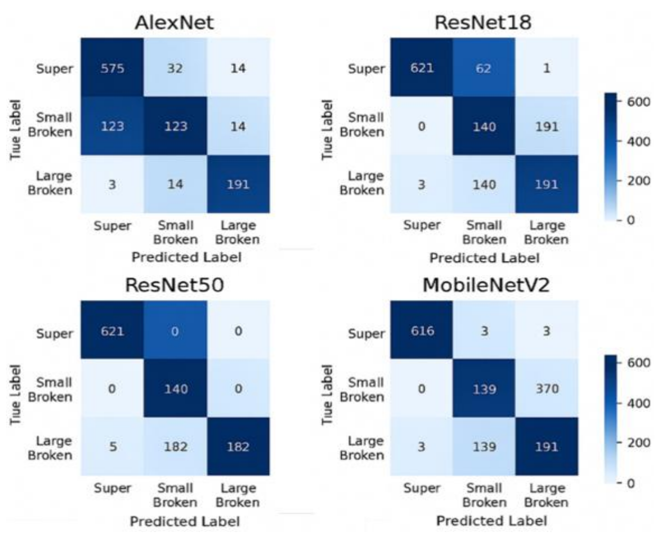


Figure 5. Confusion matrix of different classifications

Table 5. Performance of the classifier

Classifier	Precision	Recall	F1-Score	Accuracy ± (95% CI)
ResNet18	0.985	0.984	0.984	0.985 ± 0.008
AlexNet	0.900	0.862	0.874	0.922 ± 0.015
MobileNetV2	0.970	0.970	0.970	0.980 ± 0.010
ResNet50	0.986	0.986	0.985	0.991 ± 0.007

Note: CI = Confidence intervals, computed using bootstrapping with 100 runs.

Table 6. Time elapsed and loss of classifier

Classifier	Time Elapsed	Loss (95% CI)
ResNet18	13 minutes 52 seconds	0.2791 ± 0.012
AlexNet	7 minutes 3 seconds	1.0002 ± 0.045
MobileNet V2	12 minutes 52 seconds	1.0677 ± 0.038
ResNet50	4 hours 14 minutes 2 seconds	0.1017 ± 0.009

Note: CI = Confidence intervals, computed using bootstrapping with 100 runs.

ResNet18 achieved an accuracy of 0.985 and an F1-score of 0.984, slightly below ResNet50 but still demonstrating high precision and recall. Its residual connections help mitigate vanishing gradient issues [10], contributing to stable performance. Nevertheless, its shallower depth compared to ResNet50 may limit representational capacity in more complex feature spaces.

AlexNet, while historically important in the development of CNNs, recorded the lowest performance among the four models (accuracy 0.922, F1-score 0.874). The confusion matrix revealed higher misclassification rates, particularly between the small broken and large broken categories. This outcome aligns with recent comparative analyses that emphasize AlexNet's limitations in fine-grained classification tasks due to its shallow architecture and absence of residual learning [47].

Training time and loss values were further examined to assess computational efficiency and convergence quality (Table 6). The results reveal a clear trade-off between model depth and training cost: deeper models achieved lower loss but required longer training durations.

ResNet50 demonstrated the most effective convergence, reaching the lowest loss value of 0.1017, though training extended to 4 hours 14 minutes. Its deep residual architecture enables superior feature extraction and generalization, but the high parameter count demands more iterations to stabilize gradients [48]. ResNet18, with fewer layers, completed training in 13 minutes 52 seconds and produced a moderate loss of 0.2791. While faster, its reduced depth limited its ability to capture complex patterns [49]. MobileNetV2, designed for efficiency, trained in 12 minutes 52 seconds but yielded the highest loss (1.0677), reflecting its emphasis on speed over precision [50]. AlexNet trained the fastest (7 minutes 3 seconds) but produced a relatively high loss, underscoring the constraints of its simple architecture in multi-class classification scenarios [51].

3.3 Real-time classification performance

A comparative analysis was carried out on four CNN architectures (ResNet50, ResNet18, AlexNet, and MobileNetV2) to evaluate their performance in classifying melinjo chips under real-time conditions (Figure 6). Among these, ResNet50 achieved the strongest results, with an AUC of 0.961 and an average precision (AP) of 0.962. These values highlight its ability to separate classes effectively and maintain precision across varying recall thresholds. Similar observations have been reported in agricultural studies, where ResNet50 consistently outperforms shallower models in tasks due to its deep residual connections and robust feature extraction capacity [52-54].

ResNet18 followed closely with an AUC of 0.926 and an AP of 0.929, confirming its reliability despite having a shallower depth. Recent work on maize seed classification demonstrated that ResNet18 can achieve strong performance when image resolution and depth are carefully optimized [55]. Its balance between computational efficiency and accuracy makes it a practical choice for agricultural applications where processing speed is critical.

AlexNet, although historically important in the development of deep learning, produced moderate outcomes (AUC 0.877, AP 0.902). The absence of residual connections and limited depth restricts its ability to capture subtle differences in agricultural commodities. Recent studies in fruit grading have shown that AlexNet's performance tends to plateau compared to more advanced CNNs, particularly when precision–recall trade-offs are emphasized [56, 57].

MobileNetV2 recorded the lowest curve metrics (AUC 0.811, AP 0.845), reflecting its lightweight design optimized for speed and resource efficiency. While this architecture is advantageous for embedded agricultural systems, its reduced representational capacity limits precision in complex classification tasks. Similar limitations have been observed in crop disease detection, where MobileNetV2 achieved faster inference times but lower accuracy than deeper CNNs [58].

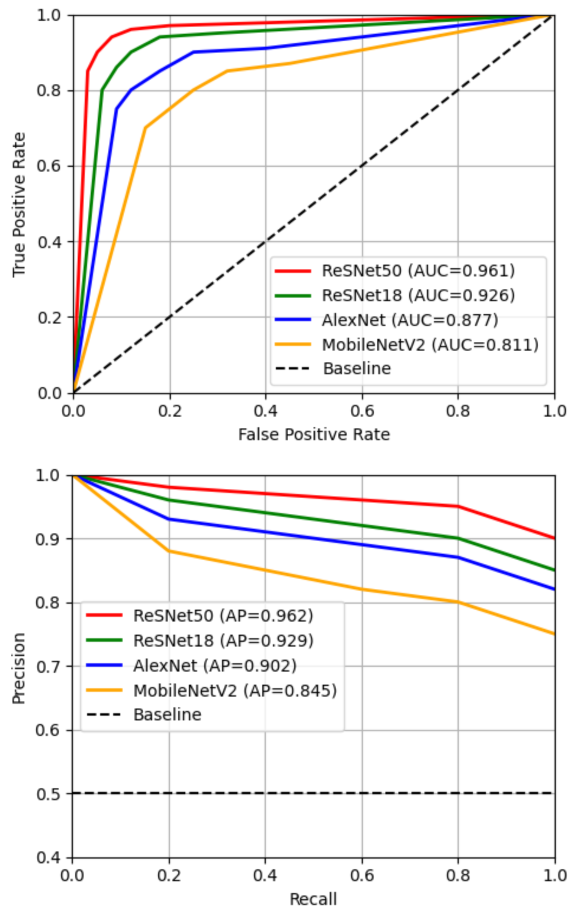


Figure 6. Area under the curve (AUC) of receiver operating characteristic (ROC) and precision-recall (PR) curves

Large broken detected

Small broken detected

Figure 7. Example of real-time classification of a melinjo chips sample using MVTec Halcon software

Table 7. Inference time real-time classification

Classifiers	Inference Time (ms)	95% CI (ms)
ResNet50	50.22	±2.10
ResNet18	32.18	±1.75
AlexNet	28.17	±1.60
MobileNet V2	18.15	±1.20

Note: CI = Confidence intervals, computed using bootstrapping with 100 runs.

The efficiency of deep learning models in agricultural applications depends not only on predictive accuracy but also on their inference time, which determines the feasibility of real-time deployment. In the case of melinjo classification, inference time reflects how quickly a trained network processes new images and delivers reliable predictions (Figure 7).

This factor is critical for practical agricultural systems such as automated grading, sorting, and quality inspection, where throughput and latency directly influence productivity. Our results highlighted that ResNet50, although offering high classification fidelity, required longer inference times, making it less suitable for edge-based systems (Table 7). ResNet50 demonstrated superior accuracy largely because of its deeper architecture and the larger number of parameters it employs. This design enables the network to learn complex and highly discriminative features from the dataset, allowing for more precise classification [59]. At the same time, the increased depth comes with a computational burden, which explains the longer inference times observed. In contrast, MobileNetV2 achieved the fastest inference speed due to its lightweight structure. The model relies on depthwise separable convolutions and an efficient bottleneck mechanism, both of which substantially reduce the number of operations required during prediction. These architectural innovations make MobileNetV2 particularly suitable for embedded agricultural applications where rapid decision-making is critical [60]. The results highlight a clear trade-off between accuracy and speed, reflecting the fundamental design differences of the two models. Selecting the appropriate architecture, therefore, depends on the operational requirements of the agricultural system in question. This interpretation aligns with recent studies showing that deeper residual networks, such as ResNet50, consistently outperform earlier CNNs in terms of accuracy because of their ability to capture complex hierarchical features [61]. Conversely, MobileNetV2's streamlined design, based on depthwise separable convolutions and bottleneck layers, has been shown to lower computational cost and inference time, making it well-suited for real-time deployment on resource-constrained platforms [62].

Recent advances in agricultural research highlight the growing importance of lightweight deep learning architectures for real-time deployment. Models optimized for inference speed can significantly enhance decision-making in precision crop protection, allowing timely interventions in the field [63]. In a similar vein, another study emphasized that striking a balance between computational efficiency and predictive accuracy is essential for sustainable automation in agriculture, particularly when operating under resource constraints [64]. Another study also introduced LiSA-MobileNetV2, an extremely lightweight model for rice disease classification, showing that inference efficiency directly impacts scalability when handling large datasets [65]. Further study validated the role of MobileNetV2 in intelligent agriculture, reporting that lightweight architectures can maintain accuracy while reducing computational costs [66]. More recently, modified MobileNetV2 networks have made it possible to find tomato diseases in real time. This shows that inference time is just as important as accuracy when choosing models for agricultural use [12].

4. CONCLUSIONS

The study confirms that CNN-based approaches can effectively classify melinjo chips, with ResNet50 emerging as the most accurate and reliable model. Its deep residual connections enable robust feature extraction and generalization, though this comes with higher computational cost and longer inference times. ResNet18 provides a practical compromise, offering strong accuracy with reduced training duration. MobileNetV2, designed for efficiency, is particularly well-suited for real-time and embedded agricultural applications where rapid decision-making is critical. AlexNet, while foundational in the history of deep learning, demonstrated limited capability in fine-grained agricultural classification tasks.

It is important to recognize certain limitations of this study. The dataset employed was relatively modest in size and collected within a controlled acquisition setting, which may not fully reflect the variability encountered under real agricultural conditions. In addition, potential class imbalance could have influenced the training process and model performance, particularly in minority categories. These constraints indicate that, while the findings are promising, they should be interpreted with caution when considering broader applications.

Overall, the results emphasize that model selection in agricultural contexts should balance predictive accuracy, generalization ability, and inference speed. Deeper architectures such as ResNet50 are preferable for high-fidelity classification, while lightweight models like MobileNetV2 are advantageous for real-time deployment in resource-constrained environments. These insights contribute to the development of scalable and efficient deep learning solutions for commodity grading and quality inspection in precision agriculture.

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