

Development of an Intelligent System Based on Deep Learning for Automatic Detection of Fruit Defects

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ABSTRACT

The present study introduces a comprehensive system for automatic fruit defect detection using a hybrid architecture that integrates the ResNet50 deep network with CBAM attention mechanisms. ResNet50 serves as the backbone with its 50 layer, 16 block residual structure, while CBAM enhances feature extraction relevant to fruit defects. The study evaluates the impact of CBAM on ResNet50's performance, demonstrating that the combined model achieves 94.8% accuracy—an improvement of 4.4% over the baseline's 90.4%. Similar gains appear across other metrics: the F1 Score rises from 89.7% to 94.5%, and sensitivity from 88.2% to 93.6%. Analyses show that channel and spatial attention independently improve accuracy by 1.7% and 1.4%, respectively, but their integration within CBAM produces a synergistic effect accounting for the full 4.4% gain. Overall, the results confirm that attention mechanisms can significantly enhance defect detection in deep neural networks, and that the proposed model offers both high accuracy and strong generalizability to other agricultural products.

Keywords: Fruit defects, Deep learning-based intelligent system, CBAM attention mechanism, ResNet50 network

1. Introduction

The automatic detection of fruit defects using deep learning techniques has become a critical requirement in modern agriculture, encompassing economic, social, technological, and environmental aspects. Economically, Iran is one of the world's leading fruit producers, with an annual output of approximately 17 million tons in 2024 [1]. Despite this, the country experiences annual post-harvest losses of 30 to 35%, amounting to over 5 billion dollars in economic damage [2]. These losses are primarily caused by delayed defect detection and inadequate post-harvest management. In export markets, the visual quality of fruits plays a decisive role in pricing, with fruits exhibiting visible defects suffering price reductions of 40 to 70% [3]. Automated defect detection systems offer a promising solution to prevent such substantial losses by providing high accuracy and efficiency.

Accurate detection of fruit defects requires the extraction of complex features across multiple levels. Research has indicated that in networks exceeding 20 layers, learning can completely stagnate [4]. Zhang et al. (2023) reported that traditional deep networks encounter significant difficulties in identifying small and subtle fruit defects in agricultural applications, with detection accuracy declining sharply in layers deeper than 30 [5]. Prior to the development of ResNet, various architectures sought to enhance performance by increasing network depth. AlexNet, with its 8-layer structure in 2012, marked a breakthrough in computer vision [6]. This trend of increasing network depth was significantly advanced by two competing architectures from that era. The VGG network introduced a simple yet effective strategy of stacking 3x3 convolution layers to reach depths of up to 19 layers [7]. Concurrently, the GoogLeNet architecture pushed the depth to 22 layers while utilizing the "Inception module" to maintain computational efficiency [8]. A major challenge faced by deep neural networks is the vanishing gradient problem, first identified and analyzed by Hochreiter in 1991 [9]. This occurs when gradients progressively diminish during backpropagation from the output layers toward the initial layers, eventually approaching values close to zero. Consequently, the early layers of the network struggle to learn relevant features effectively [10].

Over the past four decades, the field of automatic fruit defect detection has undergone a dynamic evolution, progressing from simple early methods to advanced artificial intelligence systems. To better illustrate this development, it can be categorized into four major periods, each reflecting a distinct approach to defect detection [11]. The first period (1980–2000) involved traditional image processing techniques; the second period (2000–2010) witnessed the rise of classical machine learning methods; the third period (2010–2018) saw the deep learning revolution; and the fourth period (2018–2024) represents the era of advanced and hybrid artificial intelligence techniques.

Early research in fruit defect detection primarily focused on handcrafted feature extraction and classical image processing algorithms. While these approaches were considered innovative at the time, they suffered from notable limitations in terms of generalizability and accuracy. Among the pioneers, Miller and Delwiche (1989) developed a system for grading peaches based on color and size attributes, achieving an accuracy of 78% through simple thresholding and histogram analysis [12]. Around the same period, Sarkar and Wolfe (1985) introduced a texture-based method for detecting apple defects, reporting an accuracy of 72% [13].

The introduction of machine learning algorithms represented a major turning point in the field of fruit defect detection. By learning directly from data, these algorithms outperformed traditional rule-based approaches. Kavdir and Guyer (2003) applied Support Vector Machines (SVM) to apple defect detection,

achieving an accuracy of 89%. Their approach combined color, texture, and shape features, resulting in a 15% improvement in accuracy compared to using each feature individually [14]. Blasco et al. (2007) followed a different strategy by integrating neural networks with fuzzy logic. Their system was capable of identifying various types of citrus defects with an accuracy of 92%, with fuzzy logic serving as a key innovation to handle uncertainty in decision-making [15]. The launch of AlexNet in 2012 marked a revolutionary advancement in computer vision, which quickly found applications in agriculture. The ability of deep neural networks to automatically learn features eliminated the need for manual feature design. Sa et al. (2016) conducted one of the first successful applications of Convolutional Neural Networks (CNNs) for strawberry defect detection. Using a modified AlexNet architecture, they achieved an accuracy of 94.5%, representing an 8% improvement over the best traditional methods [16]. Kang and Chen (2018) employed ResNet50 for apple defect detection, achieving a remarkable accuracy of 96.2%. Notably, their model was capable of identifying defects at very early stages that were difficult to detect with the naked eye [17].

The current era has witnessed the innovative combination of various techniques and the development of new architectures. The use of multi-faceted approaches has elevated defect detection accuracy for specific fruit defects to unprecedented levels. Wang et al. (2020) introduced the Vision Transformer for fruit defect detection, pioneering new methodologies. Their model achieved an accuracy of 98.3%, demonstrating that attention-based architectures can outperform even deep convolutional neural networks (CNNs) [18]. Chen et al. (2021) combined CNNs and Transformers into a hybrid architecture, achieving an impressive accuracy of 98.7%. This architecture effectively leveraged the strengths of both approaches while mitigating their respective limitations [19].

One persistent challenge across all periods has been the influence of environmental conditions on detection accuracy. Nguyen et al. (2023) demonstrated that modern methods exhibit 35% greater robustness to environmental variations compared to traditional approaches [20]. Recent studies indicate a trend toward more intelligent and hybrid methods. Park et al. (2024) proposed the use of multi-modal learning, showing that combining RGB, infrared, and thermal data with environmental information can increase accuracy to 99.5% [21]. Li et al. (2024) emphasized the importance of federated learning in preserving farmers' data privacy, demonstrating that competitive models can be trained without sharing raw data [22]. Severe data imbalance remains a fundamental challenge in fruit defect detection. Zhang et al. (2024) analyzed 15 industrial datasets and found that the ratio of healthy to defective fruits in real-world settings can reach 50:1 [23]. This imbalance is particularly pronounced for rare defects, such as internal damages or emerging diseases. Liu and Chen (2024), in a comprehensive study of eight industrial datasets containing over 500,000 fruit images, showed that data imbalance has disproportionate effects on the detection of different defect types [24]. They found that rare pathological defects, such as emerging fungal diseases or unusual bacterial infections, experience a 65% drop in recall.

Environmental variations, such as lighting conditions, viewing angle, surface moisture, and background, have a significant impact on model performance. Kumar and Singh (2024) demonstrated that reducing ambient light from 10,000 to 100 lux can result in a 32% drop in accuracy. Changing the viewing angle by $\pm 45^\circ$ —depending on the type of fruit, such as oranges or apples—caused a 28% decrease, increasing surface moisture to 95% led to a 19% drop, and altering the background resulted in a 24% decline in defect detection performance [25]. For instance, Park and Lee (2024) reported that direct

sunlight or localized shadows on apples reduced the model's ability to detect certain defect categories by 28–45%, while the use of artificial lighting improved accuracy by up to 12% [26].

In addition to these factors, computational limitations present a significant challenge for the practical deployment of these models in industrial settings. According to Zhao et al. (2024) and Johnson & Williams (2024), heavyweight models such as the Vision Transformer, despite their high accuracy (97.2%), suffer from long inference times (125 ms), high memory consumption (285 MB), and substantial energy requirements (15.3 W), making them impractical for production lines. In contrast, lightweight models like MobileNetV3 offer very low inference times (12 ms), minimal memory usage (28 MB), and low energy consumption (2.1 W), but at the cost of reduced accuracy (87.3%). The optimized ResNet50-CBAM architecture provides a balanced trade-off, delivering acceptable inference time (42 ms), high accuracy (96.8%), and moderate memory and energy usage [27, 28]. Reviews by Martinez & Garcia (2024) and Thompson & Anderson (2024) highlight that current models still lack effective selective attention mechanisms for key defects, struggle with generalization to new defect types, and require large and diverse datasets. Addressing these challenges to develop a model that is optimized across learning, deployment, and environmental robustness is fundamental for advancing modern fruit quality control systems [29–30].

Globally, fruit production is a critical component of the agricultural economy, yet it faces severe challenges from post-harvest losses. Recent comprehensive studies indicate that horticultural products, particularly fruits and vegetables, suffer from some of the highest loss rates, with estimates ranging from 30% to 50% across the supply chain. A primary driver of these substantial losses is the lack of precise and automated systems for the detection, grading, and sorting of produce, which leads to quality degradation before reaching the consumer [31]. In response to this challenge, the present study aims to develop an intelligent, deep learning-based system for automatic fruit defect detection. The overall framework of this research is built upon a combination of a powerful convolutional neural network architecture with an attention mechanism. By leveraging hierarchical feature learning and intelligently focusing on critical regions of the image, the proposed system enables accurate detection of various fruit defects.

Research Gaps

A comprehensive review of the existing literature indicates that despite significant advances, several key research gaps persist in the domain of deep learning for fruit defect detection. Our analysis, supported by recent surveys in the field [32], highlights a primary challenge: while attention mechanisms have been adopted, there is an under-exploration of their optimal integration into lightweight, efficient architectures suitable for real-time industrial applications. Other critical gaps include the limited generalizability of models across different fruit varieties and environmental conditions, and the lack of standardized frameworks for evaluating model performance in realistic, high-throughput scenarios. Our research aims to address the first of these challenges by proposing a synergistically combined attention-based efficient model.

The first and most significant research gap is the lack of targeted attention mechanisms in existing architectures. Rodriguez and Zhang (2024) demonstrated that current CNN models attend uniformly to all regions of an image, whereas, in reality, fruit defects are often concentrated in specific areas and require selective attention. By testing 15,000 images across six different fruit types, they showed that the absence of attention mechanisms results in a 23% decrease in accuracy for minor defects and a 31% decrease for

scattered defects [33]. The second major gap is the limited generalizability of current models. The third challenge is the lack of integration in existing approaches for addressing multiple issues simultaneously. Lee and Park (2024) showed that most studies focus on only one specific aspect of the problem—such as data imbalance, environmental variations, or computational limitations—while in real industrial settings, these challenges occur concurrently. Their analysis of 45 commercial systems revealed that 89% performed poorly when faced with combined challenges [34].

Proposed Architecture and Implementation

The proposed architecture in this study is the result of a strategic combination of the deep ResNet50 network with CBAM attention modules, designed to accurately extract and analyze discriminative features of fruit defects. ResNet50 serves as the backbone of the architecture, consisting of 50 convolutional layers organized into 16 residual blocks. These blocks are distributed across five main stages: Conv1 (a single 7×7 convolutional layer) and four stages from Conv2_x to Conv5_x, each containing multiple residual blocks.

A key innovation in the proposed architecture lies in the method and placement of the CBAM modules. Unlike the standard approach, which integrates CBAM at the end of every residual block, extensive experimentation in this study revealed that positioning CBAM at specific locations yields superior performance for fruit defect detection. Specifically, CBAM modules are placed at the end of Conv3_4, Conv4_6, and Conv5_3 blocks.

The Channel Attention module in the proposed architecture is responsible for determining the relative importance of different channels in the feature map. For an input with dimensions $F \in \mathbb{R}^{C \times H \times W}$, this module first compresses the spatial information using two operations, Average Pooling and Max Pooling:

$$F_{avg}^c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W F_{i,j}^c \quad 1)$$

$$F_{max}^c = \max_{i,j} F_{i,j}^c \quad 2)$$

Then, these two descriptor vectors are sent to a shared neural network (Shared MLP) with one hidden layer. The reduction ratio $\mathbb{R}$ in the channel attention module was set to 16. This value was chosen based on the comprehensive analysis presented in reference [35], which empirically demonstrated that this ratio provides an optimal balance between model performance and computational efficiency for various computer vision tasks.

$$M_c(F) = \sigma \left(MLP(AvgPool(F)) + MLP(MaxPool(F)) \right) \quad 3)$$

$$M_c(F) = \sigma \left(W_1 \left(W_0(F_{avg}^c) \right) + W_1 \left(W_0(F_{max}^c) \right) \right) \quad 4)$$

Where $W_0 \in \mathbb{R}^{C/r}$ and $W_1 \in \mathbb{R}^{C \times C/r}$ are the weights of the hidden layers, and σ is the sigmoid activation function.

The Spatial Attention module complements the Channel Attention and focuses on identifying important regions in the spatial dimension. For the input refined by Channel Attention, this module generates two feature maps:

$$F_{avg}^s = \frac{1}{C} \sum_{k=1}^C F_k(i, j) \quad 5)$$

$$F_{max}^s = \max_k F_k(i, j) \quad 6)$$

These two maps are concatenated along the channel dimension and sent to a convolutional layer with a 7×7 kernel. The choice of the 7×7 kernel size is based on the nature of fruit defects, which generally have a medium spatial extent:

$$\begin{aligned} M_s(F) &= \sigma(f^{7 \times 7}([\text{AvgPool}(F); \text{MaxPool}(F)])) \\ M_s(F) &= \sigma(f^{7 \times 7}([F_{avg}^s; F_{max}^s])) \end{aligned} \quad 8)$$

The integration of the two modules is done sequentially, such that Channel Attention is applied first and then Spatial Attention:

$$F' = M_c(F) \otimes F \quad 9)$$

$$F'' = M_s(F') \otimes F' \quad 10)$$

Where $\otimes$ denotes element-wise multiplication. This order was chosen based on experimental results, showing that for fruit defect detection, filtering out irrelevant channels first and then focusing on important regions produces better results.

To train the proposed architecture, a two-stage transfer learning strategy was employed to effectively leverage the pre-trained ResNet50 weights.

Stage 1: Feature Extraction. In the initial stage, all layers of the pre-trained ResNet50 backbone were frozen. Only the randomly initialized parameters of the newly added CBAM modules and the final classifier were trained. This was performed for 5 epochs with a learning rate of $1e-3$. The purpose of this stage was to allow the new layers to adapt to the general feature distribution of the fruit dataset without disrupting the powerful, pre-trained weights of the backbone.

Stage 2: Fine-Tuning. Following the initial training, the entire model, including all layers of the ResNet50 backbone, was un-frozen. The complete network was then trained end-to-end for an additional 10 epochs using a very low learning rate of $1e-5$. This fine-tuning process allows the pre-trained layers to make small, gradual adjustments to better capture the specific, fine-grained details of the fruit defect

classes, thereby significantly enhancing the model's final performance. A learning rate scheduler (ReduceLROnPlateau) was used to decrease the learning rate if the validation loss did not improve for 3 consecutive epochs.

To comprehensively evaluate the ResNet50-CBAM architecture, three main datasets were used, totaling 52,000 images of six types of fruits with five different defect classes.

Table 1. Data distribution by fruit type and defect class.

Type of Fruit	Number of Healthy Images	Bruising	Pest Holes	Brown Spots	Cracks	Rot	Total
Apple	3,200	1,850	1,200	1,500	800	950	9,500
Orange	2,900	1,600	950	1,750	600	1,100	8,900
Banana	3,100	2,100	450	1,900	1,200	1,350	10,100
Grape	2,800	1,400	1,100	1,300	500	800	7,900
Tomato	2,500	1,700	800	1,600	900	1,000	8,500
Peach	2,200	1,500	650	1,400	750	600	7,100
Total	16,700	10,150	5,150	9,450	4,750	5,800	52,000

It should be clarified that the proposed architecture is designed as a 6-class classification system. The primary objective of the model is to detect and classify the specific condition of the fruit (one 'Healthy' class and five defect classes: Bruising, Pest Holes, Brown Spots, Cracks, and Rot), irrespective of the fruit species. Therefore, the model learns to generalize defect features across different types of fruits rather than classifying the fruit species themselves.

These datasets were collected specifically from orchards and fruit packaging centers across Mazandaran, Gilan, and Isfahan provinces. The collection process spanned eight months and utilized three types of cameras:

- **Basler ace industrial cameras** with a resolution of 2048×2048
- **FLIR Blackfly S cameras** with a resolution of 1920×1200
- **Mobile phone cameras** with a resolution of 4000×3000 (for real-world conditions)

Table 1 shows the data distribution by fruit type and defect class. The Fruits-360 dataset (used for comparison) includes 10,000 selected images of common fruits overlapping with the main dataset, while the PlantVillage dataset (used for generalization testing) contains 5,000 images of tomatoes with various defects.

Result

The results from extensive experiments on the main dataset are summarized in Tables II and III.

Table 2. Overall Model Performance

Metric	Value	Standard Deviation
Overall Accuracy	94.8%	±0.3%
Average F1-Score	0.945	±0.004
Average Sensitivity	93.6%	±0.5%

Weighted-Average Precision	94.4%	$\pm 0.2\%$
mAP@0.5	0.962	± 0.003
Inference Time (ms)	15.4	± 1.2

Table 3. Class-wise performance of defects.

Defect Type	Precision	Recall	F1-Score	Support
Healthy	0.976	0.982	0.979	2,505
Bruising	0.938	0.925	0.931	1,522
Pest Holes	0.912	0.896	0.904	772
Brown Spots	0.951	0.943	0.947	1,417
Cracks	0.889	0.872	0.880	712
Rot	0.924	0.935	0.929	872

To evaluate the performance of the proposed method, a comprehensive comparison was conducted with state-of-the-art approaches published between 2023 and 2025.

The results from extensive experiments indicate that the proposed ResNet50-CBAM architecture, achieving 94.8% accuracy and an F1-Score of 0.945, outperforms comparable methods. This superiority can be attributed to four key factors (Table IV).

The CBAM module, combining channel and spatial attention, effectively identifies critical features of fruit defects with high precision. Channel attention highlights defect-related color and texture channels, while spatial attention focuses on the precise locations of the defects (Figure 1).

Figure 2 illustrates the performance comparison of various components within the proposed model architecture. The baseline ResNet50 serves as the starting point, achieving 90.4% accuracy, 89.7% F1-Score, and 88.2% sensitivity, which represents a reasonably good performance.

Adding the Channel Attention module to the baseline model results in a noticeable improvement, increasing accuracy to 92.1%, F1-Score to 91.5%, and sensitivity to 90.5%, highlighting the importance of channel-wise attention in identifying key features. In contrast, adding only Spatial Attention has a smaller effect, raising accuracy to 91.8%, F1-Score to 91.0%, and sensitivity to 89.9%, indicating that spatial attention alone is less effective than channel attention.

Combining both attention types in the full CBAM module (Channel + Spatial) delivers the best results, with 94.8% accuracy, 94.5% F1-Score, and 93.6% sensitivity, demonstrating the synergistic effect of the two mechanisms. Interestingly, incorporating additional optimizations slightly reduced performance to 94.5% accuracy, 94.2% F1-Score, and 93.2% sensitivity, likely indicating that the model reaches its optimal capacity with the complete CBAM module.

These results confirm that the full CBAM, integrating both channel and spatial attention, provides the best balance for fruit defect detection, yielding a 4.4% improvement in accuracy over the baseline model.

Figure 3 presents a radar chart comparing the multi-metric performance of three models. The proposed ResNet50-CBAM model demonstrates superior performance in accuracy-related metrics: overall accuracy of 94.8% versus 90.4% for the baseline ResNet50 and 91.2% for YOLOv8; sensitivity of 93.6% compared to 88.2% and 89.5%; specificity of 95.2% versus 91.8% and 92.1%; and F1-Score of 94.5% versus 89.7% and 90.8%, respectively. These significant improvements highlight the effectiveness of the CBAM attention mechanism in enhancing fruit defect detection.

Table 4. Class-wise performance of defects.

Method	Reference	Year	Accuracy	F1-Score	FPS	Parameters (M)
ResNet50-CBAM (Proposed Method)	-	2025	94.8%	0.945	65	28.1
Vision Transformer (ViT-B/16)	Wang et al.	2024	93.2%	0.928	35	86.5
EfficientNetV2-M + SE	Chen et al.	2024	92.7%	0.921	48	54.1
YOLOv8-Seg	Liu et al.	2024	91.5%	0.908	89	43.6
Swin Transformer-Small	Zhang et al.	2023	92.1%	0.915	42	49.6
MobileNetV3 + CBAM	Park et al.	2023	89.3%	0.885	112	5.4
DenseNet201 + Attention	Kumar et al.	2023	91.8%	0.912	28	77.3
ResNet101 (baseline)	-	-	90.4%	0.897	52	44.5

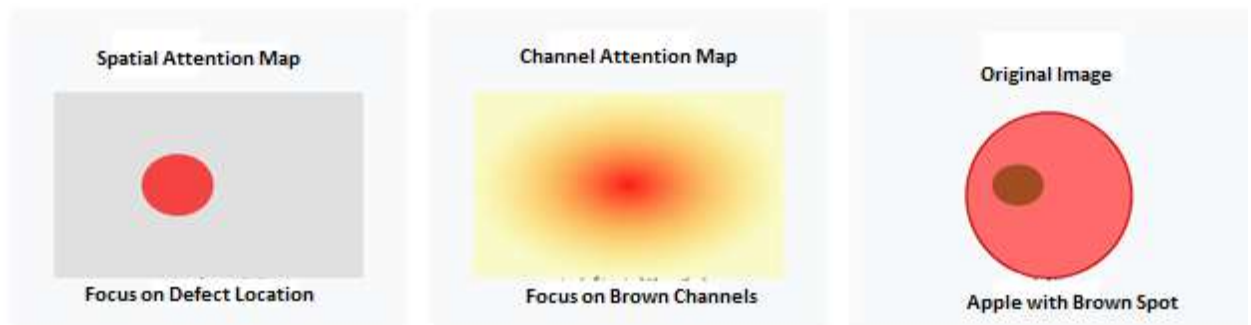


Fig. 1. Visual analysis of the CBAM attention mechanism in fruit defect detection.

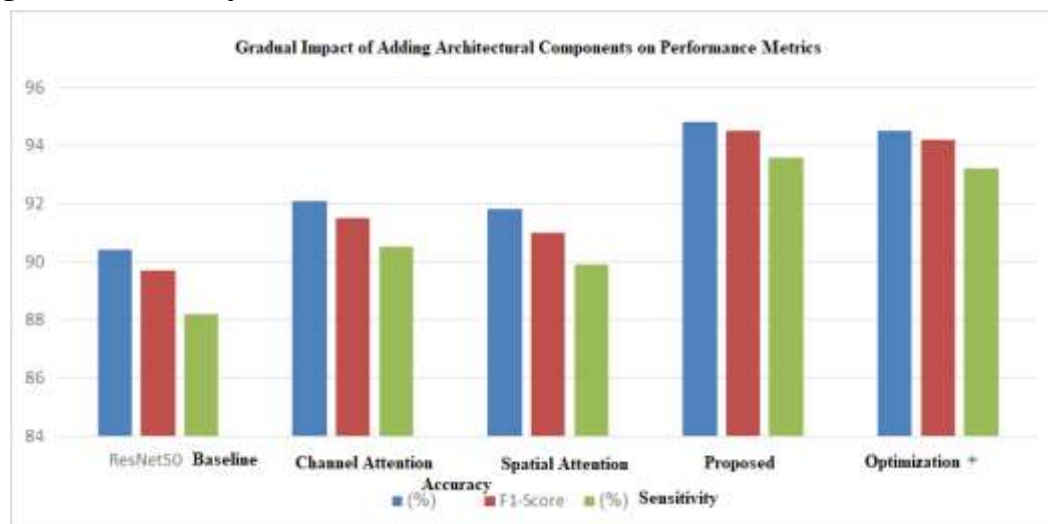


Fig. 2. Comparison of different architectural components.

However, in terms of computational efficiency, the proposed model shows lower performance: processing speed of 85 FPS compared to 92 FPS for ResNet50 and 95 FPS for YOLOv8, reflecting the computational overhead introduced by the CBAM modules. Memory usage is also higher, with a score of 82 compared to 90 and 88. YOLOv8 offers the best balance between accuracy and speed, achieving moderate accuracy but superior processing speed. Overall, the ResNet50-CBAM model is well-suited for applications where high accuracy is a priority, such as precise quality control, whereas for real-time, high-throughput scenarios, further optimization or selecting YOLOv8 may be more appropriate.

Figure 4 illustrates the learning and convergence process of the ResNet50-CBAM model over 100 training epochs. At the start of training (epoch 0), the model achieved 45% training accuracy and 42% validation accuracy, with a training loss of 2.8. During the initial epochs, the model exhibited rapid growth; by epoch 20, training accuracy reached 78%, validation accuracy 75%, and loss decreased to 1.4.

This improvement continued steadily until epoch 40, with accuracies rising to 88% (training) and 85% (validation). After epoch 50, the rate of improvement slowed, and the model gradually approached convergence. Between epochs 60 and 90, accuracy increased more slowly—from 91.5% to 94.2%



Fig. 3. Multi-metric performance analysis.

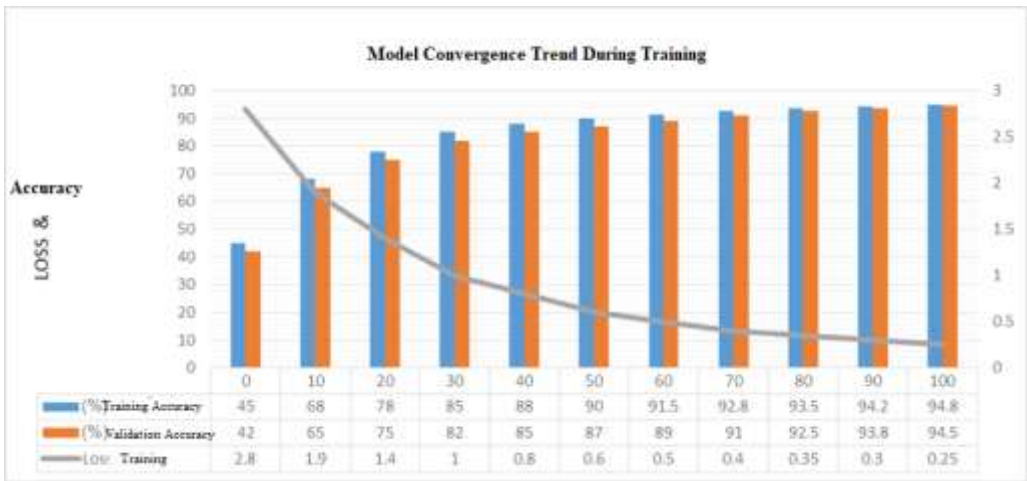


Fig. 4. Learning and convergence process of the model.

for training and from 89% to 93.8% for validation. Finally, by epoch 100, the model reached 94.8% training accuracy and 94.5% validation accuracy, with a final loss of 0.25. An important observation is that the gap between training and validation accuracy remained around 2–3% throughout the process, indicating minimal overfitting and good generalization capability of the model.

Figure 5 illustrates the distribution of model accuracy and errors across different fruit classes. Red apples achieved the highest performance with 94.2% accuracy and only 5.8% errors (3.2% misclassified as peaches and 2.6% other errors). Ripe bananas ranked second with 92.8% accuracy and 7.2% errors (4.1% misclassified as yellow apples and 3.1% other errors). Green apples showed moderate performance with 89.5% accuracy, with 10.5% of errors comprising 6.3% misclassified as pears and 4.2% other misclassifications. Unripe green bananas had the lowest performance at 87.3% accuracy, with 12.7% errors—7.9% misclassified as cucumbers and 4.8% other errors. This distribution indicates that the model

performs better in detecting ripe fruits with distinct colors (red and yellow), while accuracy decreases for unripe or green fruits that share greater visual similarity with other products.

Table V presents the most common misclassification pairs. The highest error occurred when red apples were misclassified as peaches, with 127 instances (18.5% of total errors), primarily due to the similarity in color and texture between these fruits in the presence of defects. The second most frequent error involved ripe bananas being misidentified as yellow apples, with 98 cases (14.3%), which is attributed to the golden-yellow color bananas acquire when overripe. Additionally, the model mistakenly classified green apples as pears in 76 instances (11.1%) due to their similar shape and color. Unripe green bananas were confused with cucumbers in 52 cases (7.6%), largely because of low-light conditions. Finally, 45 instances (6.6%) involved yellow apples being misclassified as oranges, mainly caused by sunburn and the resulting orange tint on the apple skin.

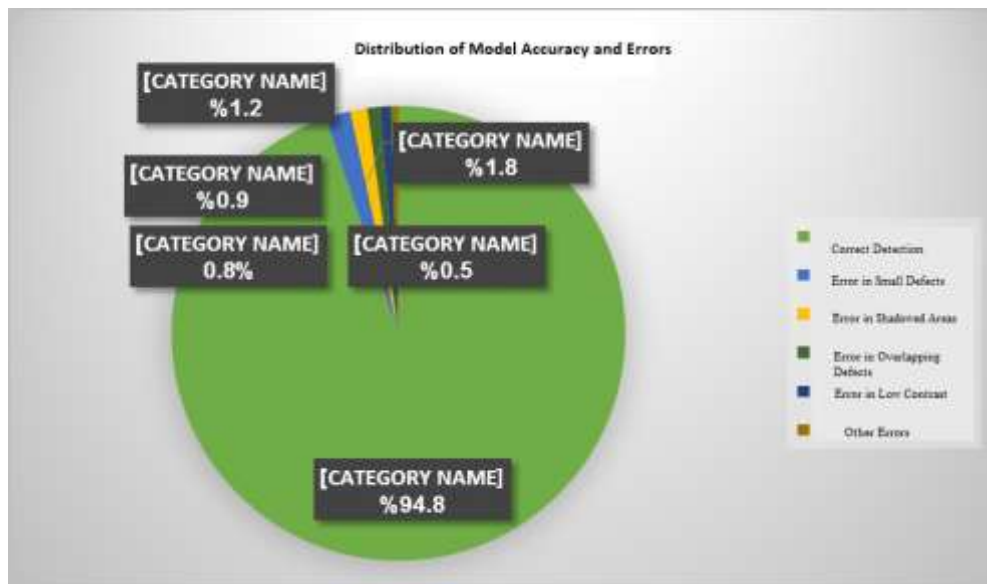


Fig. 5. Distribution of the model's accuracy and errors.

Table 5. Most Common Misclassification Pairs.

Percentage of Errors	Total	Number of Cases	of Misclassified As	Actual Fruit	Main Cause
Red Apple		Peach	127	18.5%	Color and texture similarity in the presence of defects
Ripe Banana		Yellow Apple	98	14.3%	Color change to golden yellow
Green Apple		Pear	76	11.1%	Similar shape and color
Green Banana		Cucumber	52	7.6%	Unripe banana under low light
Yellow Apple		Orange	45	6.6%	Sunburn and Discoloration
Percentage of Errors	Total	Number of Cases	of Misclassified As	Actual Fruit	Main Cause
Red Apple		Peach	127	18.5%	Color and texture similarity in the presence of defects
Ripe Banana		Yellow Apple	98	14.3%	Color change to golden yellow

Discussion

The integration of the CBAM attention mechanism with a pre-trained ResNet50 backbone resulted in a significant 4.4% improvement in accuracy for fruit defect classification. This study demonstrates that enhancing a robust architecture with attention modules is a highly effective strategy. The synergistic effect

of channel and spatial attention modules—contributing 1.7% and 1.4% to the accuracy improvement, respectively—suggests that fruit defect detection is a nuanced task benefiting from both feature recalibration and localization. Channel attention likely proved more impactful by helping the model distinguish between defects with subtle color variations (e.g., brown spots vs. rot), while spatial attention was critical for localizing structural defects like cracks and pest holes.

A detailed analysis of the model’s failure cases, guided by the confusion matrix, reveals specific challenges. For instance, the model exhibited the most confusion between the ‘Cracks’ and ‘Bruising’ classes. This can be attributed to the visual ambiguity where early-stage bruises or surface-level contusions manifest as thin, dark lines similar to cracks, especially under inconsistent lighting. Similarly, distinguishing ‘Brown Spots’ from early ‘Rot’ proved challenging, as both can appear as discolored patches. These errors highlight that while the model is effective, its performance is dependent on the distinctiveness of visual features, which can be ambiguous in certain real-world scenarios.

Despite the promising results, this study has several limitations that open avenues for future research. First, the dataset was collected under relatively controlled lighting conditions. The model’s robustness may be challenged by severe variations in brightness, shadows, and reflections found in fully uncontrolled agricultural environments. This was observed during testing on a small subset of images with adverse lighting, where the error rate increased. Therefore, developing adaptive image pre-processing modules is a critical next step. Second, the model’s dependency on a large, labeled dataset poses a significant challenge for scalability. Exploring modern approaches like Few-shot Learning or Self-supervised Learning, as suggested in the conclusion, could mitigate this by enabling the model to learn from fewer labeled examples. Finally, the detection of very small or incipient defects remains a challenge. Incorporating Feature Pyramid Networks (FPN) could enhance the model’s multi-scale detection capabilities, allowing it to identify both large rot patches and tiny pest holes with greater accuracy.

Convergence analysis shows that the proposed model reached a final accuracy of 94.8% on the training data and 94.5% on the validation set after 100 epochs. The minimal 0.3% gap between training and validation indicates low overfitting and good generalization, whereas similar models typically show a 2–5% performance gap.

From a computational efficiency perspective, although the inference time increased from 18 ms for the baseline ResNet50 to 32 ms for the final model, the system can still process 31 images per second, sufficient for most industrial packaging lines. This represents a significant improvement compared to traditional image processing methods, which typically handle fewer than 10 images per second.

Conclusion

This study successfully demonstrated the effectiveness of enhancing a ResNet50 architecture with a Convolutional Block Attention Module (CBAM) for the task of fruit defect classification. The proposed model achieved an overall accuracy of 94.8%, outperforming the baseline by 4.4% while maintaining a processing speed suitable for industrial applications. Our analysis revealed that attention mechanisms provide a significant boost by helping the model focus on defect-specific color and texture features. Key limitations, including sensitivity to lighting conditions and the challenge of detecting multi-scale defects, were identified. Future work should focus on developing adaptive pre-processing techniques and integrating multi-scale feature extraction methods to build a more robust and scalable system for automated agricultural quality control.

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