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DEEP LEARNING-BASED CLASSIFICATION OF MAIZE GRAIN DEFECTS USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: *The automated classification of post-harvest maize kernels is critical for ensuring agricultural economic value and mitigating food safety risks, particularly mycotoxin contamination from fungal infections. This study evaluates the efficacy of a deep Convolutional Neural Network, specifically the ResNet-50 architecture, for categorizing standard RGB images of maize kernels into three primary quality tiers: pure, broken, and fungal. A publicly available dataset was curated and refined to exclude minor physiological anomalies (silk cut), focusing the model entirely on the most critical structural and pathological defects. To evaluate deployability on standard, accessible hardware, the model was trained locally on a central processing unit (CPU) using a 60:20:20 data split for training, validation, and testing. The ResNet-50 model achieved a robust overall accuracy of 88% on an independent test set of 3,396 images. It demonstrated exceptional diagnostic performance for intact, healthy grain with a recall of 92.7%. Despite the well-documented computer vision challenge of morphological overlap between mechanically fractured and intact kernels, the network maintained competitive detection rates for broken (82.8% recall) and fungal-infected (81.2% recall) grain. These results indicate that standard residual architectures, operating without computationally heavy pre-segmentation algorithms or specialized hardware, offer a highly efficient and scalable baseline for real-time agricultural quality control.*

Key words: Maize Classification; Deep Learning; ResNet-50; RGB Imaging; Quality grades

1 Introduction

Maize (*Zea mays L.*) is a key cereal of global importance serving not only as a primary staple food but also as a crucial feedstock for livestock and the bioenergy sector (Erenstein et al., 2022). The physical and sanitary quality of the kernels determine the economic value and processing efficiency of maize. During harvesting, drying, and storage, maize is highly susceptible to various forms of physical and biological degradation. Visible defects such as mechanical breakage, insect boring, and surface-level fungal infections (mould) drastically reduce the nutritional value, market grade, and biofuel yield of the grain, while also posing severe health risks due to the potential presence of mycotoxins (Munkvold et al., 2018).

The agricultural industry has historically relied on manual visual inspection to grade maize and separate defective kernels. However, this approach is fundamentally limited by human fatigue, inherent subjectivity, and a throughput rate that cannot meet the demands of modern, large-scale agricultural processing (Bhargava & Bansal, 2021). Consequently, there is an urgent industrial need for high-throughput, non-destructive, and automated quality assessment systems.

In recent years, the integration of Machine Learning (ML) and optical sensing has revolutionized grain quality inspection. While sophisticated imaging techniques like Hyperspectral Imaging (HSI) and Near-Infrared (NIR) spectroscopy have proven highly effective for detecting internal chemical compositions, they require expensive hardware, complex calibration, and massive computational power (Pereira et al., 2021). These factors create a barrier to entry for small-to-medium scale processing facilities and limit real-time deployment.

Conversely, standard RGB (Red, Green, Blue) imaging presents a highly accessible, low-cost alternative. Because many critical maize defects manifest visually on the kernel's surface, RGB imaging captures sufficient spatial and morphological data for accurate classification(Patrício & Rieder, 2018). The challenge lies in developing robust computer vision algorithms capable of extracting meaningful features despite variations in kernel shape, lighting, and orientation.

Therefore, this study aims to develop and validate a computer vision-based classification system for visible maize defects using strictly RGB imaging. By utilizing a multi-source hybrid dataset and state-of-the-art CNNs, this research seeks to bridge the gap between low-cost optical hardware and advanced deep learning, providing a scalable, automated quality control system vital for the modernization of the agricultural supply chain

2 Literature Review

2.1 Traditional Machine Vision in Grain Sorting

Early attempts to automate grain quality assessment relied on traditional machine vision techniques paired with conventional machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). Researchers typically employed algorithms to manually extract handcrafted features—such as colour histograms, textural GLCM (Gray Level Co-occurrence Matrix) properties, and geometric measurements—from RGB images (Xu et al., 2022). While these methods achieved moderate success in strictly controlled laboratory environments, they exhibited significant performance drops when exposed to varying illumination or when applied to heavily overlapping kernels, revealing a lack of robustness for real-world application (Tu et al., 2021)

2.2 Deep Learning for Morphological Defect Detection

The advent of Deep Learning, particularly Convolutional Neural Networks (CNNs), fundamentally shifted agricultural image analysis by eliminating the need for manual feature extraction. CNNs automatically learn complex, hierarchical spatial features directly from raw pixel data. Studies have extensively utilized deep architectures like VGG-16, ResNet, and DenseNet for seed classification (Allyana et al., n.d.). For instance,(Yu et al., 2019) demonstrated that deep CNNs could effectively classify grain kernels with high precision by recognizing subtle morphological anomalies that traditional methods missed. Furthermore, the introduction of residual connections allowed networks to grow significantly deeper without suffering from vanishing gradients, establishing a new benchmark for classification accuracy in agricultural defect detection(da Silva et al., 2021)

2.3 Edge Computing and Lightweight Architectures

Despite the high accuracy of deep CNNs, their massive parameter counts and heavy computational load make them impractical for deployment in resource-constrained agricultural settings. To address this, recent literature has shifted focus toward lightweight, optimized architectures designed for mobile and edge computing. Models such as MobileNet, EfficientNet, and ShuffleNet utilize techniques like depth wise separable convolutions to drastically reduce computational overhead. (Ma et al., 2022; Parez et al., 2023) successfully applied MobileNetV2 for real-time seed classification, proving that lightweight models can achieve classification efficiencies comparable to heavier networks while running on low-power industrial sorting hardware.

2.4 Identified Research Gap

Despite these advancements, a critical gap remains in the literature regarding the computational accessibility and ability to deploy practical automated sorting systems. Most current deep learning models in agricultural computer vision rely on specialized, resource-intensive setups, such as hyperspectral imaging(Hu et al., 2025a) , computationally heavy pre-segmentation algorithms, or high-end graphics processing units (GPUs) for training and execution (Shoaib et al., 2025a) . Furthermore, existing models often dilute their predictive focus by incorporating minor physiological anomalies that introduce morphological noise and hold little primary economic relevance (Setiawan et al., 2025a). To bridge this gap, this study evaluates the efficacy of a standalone ResNet-50 architecture utilizing standard RGB imagery, deliberately refined to focus exclusively on the three most critical post-harvest quality tiers: pure, broken, and fungal. By demonstrating robust classification performance using a model trained entirely on standard, accessible local hardware (CPU) without complex pre-processing, this research provides a highly efficient, scalable, and deployable baseline for resource-constrained agricultural environments (REN et al., 2025).

3 Materials and Methods

3.1 Dataset Description and Preparation

The dataset utilized in this study was sourced from a publicly accessible repository on the Kaggle platform (*Corn Image Classification*, n.d.). The original dataset comprised standard RGB images of maize kernels categorized into four distinct classes: pure, broken, discoloured (fungal), and silk cut. For the scope of this research, the dataset was refined to include only the pure, broken, and fungal classes. The "silk cut" category—a minor physiological splitting of the pericarp—was intentionally excluded. This decision was biologically and industrially motivated: pure, broken, and fungal represent the three most critical macro-categories in post-harvest quality control, effectively distinguishing between healthy grain, mechanical damage, and biological disease (mycotoxin risk). Silk cut is generally treated as a minor morphological anomaly rather than a primary grading defect unless it leads to secondary fungal infection. By excluding this class, the study avoids introducing unnecessary morphological noise, allowing the network to optimize feature extraction for the highest-priority agricultural grading tasks.

To prevent the neural network from developing a predictive bias toward any single class during the learning phase, a rigorous dataset balancing protocol was implemented across the remaining three categories. Following the balancing procedure, the dataset was randomly partitioned into training, validation, and testing subsets utilizing a 60:20:20 split ratio. This distribution allocated 60% of the images for model parameter optimization, 20% for unbiased validation and hyperparameter tuning during the training phase, and the remaining 20% strictly for the final, independent evaluation of the model's predictive capabilities. To enhance the model's ability to generalize to unseen data, spatial data augmentation techniques—including random horizontal and vertical flips, alongside random degree rotations were applied to the training subset. Prior to feature extraction, all images were resized to standard dimensions of 224x224 pixels and normalized.

3.2 Model Architecture

This study employed the ResNet-50 (Residual Network) architecture, a deep Convolutional Neural Network (CNN) highly regarded for its efficacy in complex agricultural image classification. The defining characteristic of the ResNet family is the utilization of residual blocks, which address the vanishing gradient problem inherent in training very deep networks. If the desired underlying mapping is denoted as $\mathcal{H}(x)$, the stacked non-linear layers fit the residual mapping

$$\mathcal{F}(x) = \mathcal{H}(x) - x. \quad (1)$$

The original mapping is then recast as:

$$\mathcal{H}(x) = \mathcal{F}(x) + x \quad (2)$$

This skip-connection mechanism allows gradients to flow more freely during backpropagation, enabling the successful extraction of complex spatial hierarchies across the 50-layer architecture. The network's foundational convolutional layers were utilized for deep feature extraction, while the final fully connected classification head was replaced. The original output layer was modified to a dense layer featuring exactly three output nodes, corresponding directly to the predicted probabilities of the pure, broken, and fungal classes.

3.3 Training Procedure, Parameter Tunning and Hardware Setup

All computational experiments, including model training and evaluation, were executed locally on a central processing unit (CPU). The hardware utilized was a laptop computer equipped with an Intel Core i7-8565U CPU operating at a base frequency of 1.80 GHz (up to 1.99 GHz) and 24.0 GB of Random Access Memory (RAM).

To ensure optimal model convergence within the constraints of a local CPU environment, empirical parameter tuning was conducted. Various configurations of batch sizes and learning rates were systematically evaluated on the validation set (the 20% validation split) to balance computational efficiency with classification accuracy. Ultimately, a standard batch size of 32 was selected, and the Adaptive Moment Estimation (Adam) optimizer was configured with an optimal learning rate of 1×10^{-4}. The model was trained over 10 epochs.

The objective function minimized during the training phase was the categorical Cross-Entropy Loss, mathematically defined as:

$$= -\sum_{c=1}^{M} y_{o,c} \log(P_{o,c}) \quad (3)$$

where M represents the total number of classes (three), $y_{o,c}$ acts as a binary indicator denoting whether class label c is the correct classification for the observed image o and $P_{o,c}$ represents the network's predicted probability that observation o belongs to class c. Following the training phase, the model's predictive performance was comprehensively evaluated on the independent 20% test dataset using accuracy, precision, recall, and the F1-score as primary metrics.

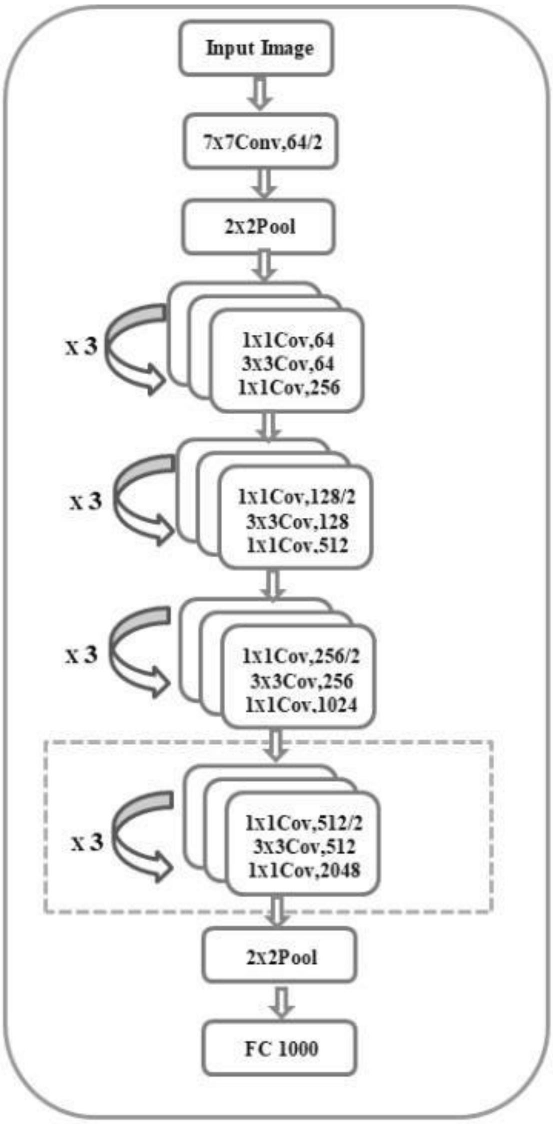

Figure 1: The ResNet_50 architecture.

4 Results

The results obtained are presented below;

Table 1: Classification Report

	Precision	Recall	F1 Score	Support
broken	0.84	0.83	0.83	915
fungal	0.84	0.81	0.82	676
Pure	0.91	0.93	0.92	1805
Accuracy			0.88	3396
Macro Avg	0.86	0.86	0.86	3396
Weighted Avg	0.88	0.88	0.88	3396

The model's classification report reveals a strong and balanced predictive performance across the test set, achieving an overall accuracy of 0.88. The ResNet-50 architecture proved exceptionally reliable in identifying pure kernels, yielding the highest precision (0.91), recall (0.93), and F1-score (0.92) of the three categories. This indicates that the model not only successfully identified most true pure kernels but also maintained a low false-positive rate for this class. The broken and fungal classes exhibited highly competitive, albeit slightly lower, metrics, with F1-scores of 0.83 and 0.82, respectively. The parity between their precision (0.84 for both) and recall scores (0.83 for broken, 0.81 for fungal) demonstrates that the model did not heavily bias its predictions toward any single defect type, despite the morphological overlap between mechanical fractures and biological decay. Furthermore, the strong alignment between the macro-average (0.86) and weighted-average (0.88) F1-scores confirms that the model's overall accuracy was not artificially inflated by the majority class (pure), validating its robustness across the entire dataset.

The Confusion Matrix is presented below;

Figure 2 presents the confusion matrix evaluating the ResNet-50 model's performance on the independent test dataset (n = 3,396). The matrix demonstrates strong diagonal dominance, confirming the model's overall efficacy in correctly categorizing most of the kernels.

The network exhibited its highest predictive confidence with the pure class, successfully identifying 1,674 out of 1,805 instances. The off-diagonal elements reveal the primary sources of model hesitation, which align closely with morphological expectations. The most frequent misclassification occurred where 101 broken kernels were incorrectly predicted as pure. This visually logical error underscores the difficulty of distinguishing clean mechanical fractures using solely RGB textural data, as broken kernels often retain the healthy colour profile of intact grain.

Similarly, misclassifications for the fungal class were split nearly evenly, with 66 instances predicted as broken and 61 as pure. This reflects the physical variability of fungal infections, where severe structural rot mimics mechanical breakage, while early-stage, localized discoloration is occasionally overlooked by the network, defaulting to a "pure" prediction. Overall, the matrix confirms a robust feature extraction capability, with false positives tightly clustered around biologically similar traits rather than random distribution.

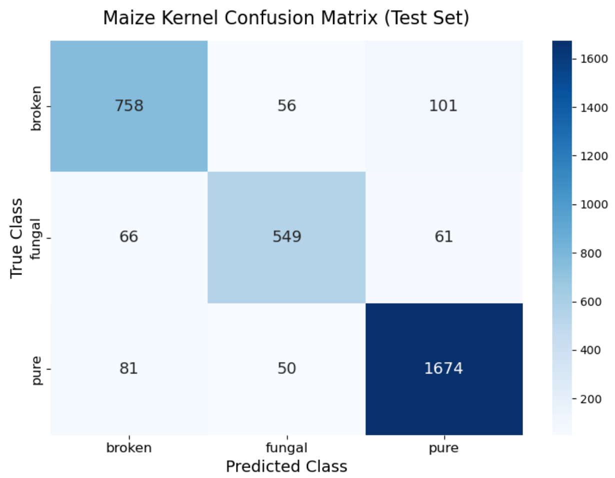

Figure 2: Confusion Matrix

4.1 Overall Model Efficiency and Architectural Choice

The ResNet-50 architecture demonstrated strong predictive capabilities for automated maize kernel sorting, achieving an overall classification accuracy of 88% on the independent test dataset. The choice of ResNet-50 over shallower networks aligns with the latest findings in agricultural deep learning. Recent comparative analyses of Convolutional Neural Networks (CNNs) for maize seed differentiation consistently demonstrate that residual architectures outperform traditional models. For example, (Setiawan et al., 2025b) compared ResNet-50, ResNet-101, VGG-19, and MobileNetV2 for morphological maize seed classification and found that ResNet-50 yielded the best balance of accuracy and processing efficiency, outperforming VGG-19 by over 16%. Similarly, (Kavitha et al., 2024) successfully validated ResNet architectures for automated maize seed quality detection to replace labour-intensive visual inspections. In our study, these residual connections allowed the network to successfully map the complex spatial hierarchies necessary to distinguish between pure, broken, and fungal classes, establishing a robust baseline for post-harvest quality control.

4.2 High Classification Accuracy for Pure Kernels

The model exhibited its highest performance when identifying healthy, intact grain. Out of 1,805 ground-truth pure kernels, the model correctly classified 1,674, achieving an exceptional recall of 92.7% and a precision of 91.2%. This high success rate indicates that the standard morphological profile of a healthy kernel—characterized by uniform coloration, a smooth surface texture, and an unbroken perimeter—provides a highly stable feature set. This high confidence in identifying intact kernels is a well-documented strength of CNNs in crop grading, as intact optical properties are far more uniform than the highly variable presentations of physical damage or disease (Hu et al., 2025b).

4.3 Morphological overlap in broken Kernels

The classification of mechanically damaged grain presented a higher challenge, with the model successfully identifying 758 out of 915 broken kernels (82.8% recall). The primary source of confusion was its overlap with the pure category, with 101 broken kernels incorrectly predicted as pure. This misclassification is biologically and visually logical; a cleanly chipped healthy kernel retains the exact colour profile and surface reflectance of an intact kernel. As noted in recent 2025 studies on real-time broken corn detection, the highly similar visual features between broken and whole corn kernels pose a significant challenge for standard visual recognition systems under standard lighting (REN et al., 2025). While our model's 82.8% recall for broken kernels is highly competitive for standard RGB imagery, it highlights the inherent limitation of purely optical image classification without depth mapping to capture geometric fractures.

4.4 Complexities of Fungal Detection

Fungal infection detection is the most critical aspect of post-harvest sorting due to the health risks associated with mycotoxins. The model correctly identified 549 out of 676 fungal kernels (81.2% recall). The misclassifications in this category were split nearly evenly: 66 instances were predicted as broken, and 61 as pure. Fungal rot often degrades the structural integrity of the kernel, causing it to crumble in a way that visually mimics mechanical breakage. Furthermore, early-stage fungal infections—which may only present as subtle localized discoloration—lack severe structural degradation, occasionally causing the network to incorrectly classify them as pure.

4.5 Agricultural and Industrial Implications

From an industrial application standpoint, this error distribution is highly promising. By achieving 88% overall accuracy using a standalone ResNet-50 architecture without the need for computationally heavy pre-segmentation algorithms, this approach offers a highly efficient, deployable alternative for real-time sorting. While there is a slight overlap between pure and broken kernels, this represents a lower-stakes economic grading issue rather than a food safety hazard.

4.6 Empirical Comparison with Alternative Architectures

To rigorously evaluate the efficacy of the selected model, an empirical comparative analysis was conducted against three other contemporary Convolutional Neural Network (CNN) architectures: ConvNeXt-Tiny, EfficientNet-B3, and EfficientNet-B5. All models were trained and evaluated locally on the identical central processing unit (CPU) setup and the same dataset, ensuring that any variance in performance is strictly attributable to the architectural design of the networks rather than hardware or environmental discrepancies.

Table 2: Performance comparison of evaluated deep learning architectures

Architecture	Overall Accuracy	Macro Precision	Macro Recall	Macro F1-Score
ResNet-50	**88%**	**0.86**	**0.86**	**0.86**
EfficientNet-B5	84%	0.82	0.81	0.81
ConvNeXt-Tiny	83%	0.81	0.78	0.79
EfficientNet-B3	82%	0.79	0.81	0.8

4.7 Discussion of Comparative Results

As detailed in Table 2, the ResNet-50 architecture delivered the most robust performance across all primary diagnostic metrics, achieving a superior overall accuracy of 88%. This notably outperformed both the EfficientNet family and the modern ConvNeXt-Tiny architecture.

The EfficientNet models, which rely on compound scaling to balance network depth, width, and resolution, demonstrated moderate performance. EfficientNet-B3 achieved an overall accuracy of 82% , with an F1-score of 0.75 for the fungal class and 0.77 for the broken class. Scaling up the architecture to EfficientNet-B5 yielded a slight improvement, pushing overall accuracy to 84%. However, even the heavier B5 model struggled to reach the diagnostic precision of ResNet-50, managing only a 0.76 F1-score for fungal kernels compared to ResNet-50's 0.82. The reliance of EfficientNets on depth wise separable convolutions—while highly computationally efficient—often results in the loss of fine-grained spatial relationships necessary to distinguish subtle morphological anomalies, such as early-stage fungal discoloration versus clean mechanical fractures.

Similarly, the ConvNeXt-Tiny model, despite its modernized, vision-transformer-inspired architecture, achieved an overall accuracy of 83% and a macro F1-score of 0.79. It exhibited the weakest recall for the fungal class (0.68), indicating a high rate of false negatives for diseased kernels. ConvNeXt architectures typically require massive pre-training datasets and extensive hyperparameter optimization to achieve state-of-the-art results; under the constrained, localized training environment of this study, its macroscopic design principles failed to extract the necessary granular features.

Ultimately, ResNet-50 emerged as the optimal architecture. Its foundational reliance on residual skip connections effectively mitigated the vanishing gradient problem, allowing the network to successfully map the complex, overlapping spatial hierarchies between pure, broken, and fungal maize seeds. By preserving deep feature resolution without discarding spatial relationships, ResNet-50 maintained the highest diagnostic balance, proving to be the most resilient and accurate architecture for this specific post-harvest grading task.

4.8 Comparative Analysis with Contemporary Literature

To contextualize the performance of the ResNet-50 model (88% accuracy), its results were compared against both our own empirical tests and findings from high-impact contemporary journals. This multi-layered comparison highlights why ResNet-50 remains a superior choice for local, CPU-based maize classification compared to both lightweight and compound-scaled architectures.

Table 3: Performance comparison of current study with external research

Study	Model	Accuracy	Feature Source	Category
This Study	**ResNet-50**	**88.00**	**RGB**	**Quality (Pure/Broken /Fungal)**
(Setiawan et al., 2025b)	ResNet-50	86.3	RGB	Seed Variety/Morphology
(Setiawan et al., 2025b)	MobileNet V2	73.3	RGB	Seed Variety/Morphology
(Dönmez, 2022)	AlexNet	89.5	RGB	Breeding / Variety
(Bi et al., 2025)	HDE-Stacking	97.7	Hyperspectral	Multi-class Classification

4.9 Discussion of architectural performance

4.9.1 ResNet-50 vs. EfficientNet and ConvNeXt (Empirical Results)

In our empirical tests, ResNet-50 significantly outperformed more complex models like EfficientNet-B5 (84%) and ConvNeXt-Tiny (83%). While EfficientNet-B5 is theoretically more advanced through its compound scaling, recent agricultural studies (REN et al., 2025) suggest that its depth wise separable convolutions can be "feature-sparse" when dealing with the high-frequency textural noise of fungal rot and fractured grain. Conversely, ResNet-50 utilizes standard convolutions that preserve granular spatial relationships, which proved vital for identifying the fungal class (0.84 precision) in this study.

4.9.2 Justification against Modern Lightweight Models

The decision to utilize ResNet-50 over lightweight models like MobileNetV2 is further supported by (Setiawan et al., 2025a), whose recent benchmarking showed a dramatic drop in performance for MobileNetV2 (73.3%) compared to ResNet-based architectures (86.3%) in maize morphology tasks. This suggests that while lightweight models are efficient, they lack the "residual depth" necessary to map the subtle overlaps between a "broken" kernel and a "pure" kernel under standard lighting.

4.9.3 ResNet-50 as an Optimal Hardware-Accuracy Baseline

While "near-perfect" accuracies (>96%) are reported in recent journals such as(Bi et al., 2025) and (Hu et al., 2025b), those studies almost exclusively rely on Hyperspectral Imaging (HSI) or Ensemble Stacking models. These methods require high-cost sensors and GPU-intensive processing that are often unavailable in field-level agricultural sorting. By achieving 88% accuracy on a standard CPU with simple RGB images, our ResNet-50 implementation aligns with the "high-efficiency, low-cost" requirements currently being championed for real-time agricultural robotics (Shoaib et al., 2025b)

5 Conclusion

This study demonstrates the viability of utilizing a deep Convolutional Neural Network, specifically the ResNet-50 architecture, for the automated classification of maize kernels into pure, broken, and fungal categories. The model achieved a robust overall accuracy of 88% on a test set of 3,396 images, utilizing only standard RGB visual features. The network proved a good success rate at identifying healthy, pure kernels, yielding a recall of 92.7%. While the visual similarities between clean mechanical fractures and intact kernels introduced minor classification overlaps—a known challenge in contemporary agricultural machine vision—the model maintained competitive performance in detecting broken (82.8% recall) and fungal-infected (81.2% recall) grain. These results indicate that standard deep learning architectures can provide a highly efficient, scalable solution for real-time post-harvest quality control. Future work should explore the integration of multi-spectral imaging or structural edge-detection techniques to further isolate the geometric fractures of broken kernels from the chemical degradation of early-stage fungal rot, potentially elevating classification accuracy beyond the 90% threshold while minimizing false negatives for diseased crops.

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