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Image-Based Seed Damage Detection Using a CNN Model

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***Abstract*—Accurate seed quality assessment is essential in agriculture. Several automated and machine learning-based methods have been developed to overcome the limitations of manual inspection. However, challenges such as computational complexity, scalability, and deployment on low-resource devices still persist. This work proposes an image-based seed damage detection system using an optimized Convolutional Neural Network (CNN). The proposed approach uses preprocessing techniques such as image resizing, normalization, and controlled data augmentation to enhance robustness and performance. The model is developed, trained, and evaluated using Python with TensorFlow and Keras. It enables effective classification of seeds into damaged and undamaged categories. The trained model is further converted into TensorFlow Lite format for deployment on resource-constrained edge devices. This reduces dependence on cloud-based processing. Evaluation on a balanced dataset consisting of four seed types, namely Apple, Bitter Gourd, Custard Apple, and Mosambi, demonstrates that the proposed system is reliable, scalable, and cost-effective. Performance is evaluated using accuracy, precision, recall, F1-score, specificity, and ROC–AUC, with the model achieving a training accuracy of 99.18%, validation accuracy of 90.32%, and test accuracy of 95.83%, demonstrating strong generalization performance.**

Keywords— Seed Damage Detection, Convolutional Neural Network (CNN), Deep Learning, Image Processing, Binary Classification, TensorFlow, Agricultural Automation

I. INTRODUCTION

Agriculture plays an important role in food security and economic sustainability, particularly in developing regions where crop productivity directly influences rural livelihoods. Among the various factors affecting crop performance, seed quality plays a decisive role in determining germination rate, plant vigor, and overall yield. However, in many practical scenarios, seed quality assessment continues to rely on manual visual inspection. This traditional process is time-consuming and may lead to inconsistent results, resulting in inaccurate grading and potential yield losses.

Early research efforts attempted to automate seed evaluation using basic image processing techniques such as shape and color feature extraction [1]. Subsequent studies incorporated artificial neural networks and pattern recognition methods to improve classification reliability and reduce human dependency [2]. Digital image processing approaches were further explored for seed purity analysis and defect detection [3], while structured visual analysis methods were applied to specific crop varieties to enhance classification accuracy [4]. More recent work demonstrated that computational image analysis can effectively support seed evaluation tasks under controlled conditions [5].

Despite these advancements, many conventional approaches rely heavily on handcrafted features and traditional classifiers, which often struggle to generalize across varying illumination, orientation, and texture conditions. These limitations emphasize the need for more adaptive and automated feature-learning mechanisms capable of handling real-world variability.

In this work, we present a complete software-based seed damage detection system built using a Convolutional Neural Network (CNN). Unlike traditional machine learning techniques that depend on manually extracted features, CNNs automatically learn hierarchical visual representations directly from raw image data. The proposed system is implemented as an end-to-end software pipeline comprising structured dataset management, image preprocessing, model training, performance evaluation, and deployment-ready inference modules. By leveraging deep learning for binary classification of seeds into Damaged and Undamaged categories, the system provides a consistent, scalable, and computationally efficient solution suitable for real-time agricultural applications.

II. RELATED WORK

Recent advancements in agricultural image analysis increasingly emphasize deep learning techniques for seed and crop classification. While earlier systems relied on handcrafted descriptors, modern convolutional neural networks have demonstrated superior capability in learning discriminative features directly from image data. A comprehensive deep learning study involving classification across a large and diverse set of seed types demonstrated that CNN architectures can achieve high accuracy without manual feature engineering, highlighting their scalability and robustness across diverse seed varieties [6]. This work laid a strong foundation for applying deep learning to agricultural image analysis.

Expanding on this direction, Loddo et al. proposed a CNN-based framework for seed image classification and retrieval, focusing on robustness under varying illumination conditions, background complexity, and seed orientation changes [7]. Their findings reinforced the adaptability of deep learning models in practical agricultural environments compared to conventional image processing methods.

Further research explored the integration of digital image processing and machine learning techniques to automate seed testing workflows. Saduwale et al. developed an image-based seed testing system aimed at minimizing human intervention while improving evaluation consistency [8]. Similarly, Koppad et al. investigated automated seed segregation using image analysis methods, demonstrating the feasibility of intelligent sorting mechanisms within agricultural operations [9]. Rajkumar et al. analyzed seed testing methodologies to improve cultivation efficiency through computational image processing techniques [10].

Complementing this effort, Meshram et al. introduced a structured agricultural image dataset designed to facilitate machine learning experimentation and benchmarking [11] (Meshram et al.), highlighting the importance of curated datasets in building reliable classification models. More recently, Raghavan et al. investigated seed quality determination using machine learning frameworks to automate inspection processes traditionally dependent on manual observation [12] (Raghavan et al.). Their study emphasized improvements in reliability, repeatability, and scalability achieved through algorithm-driven evaluation systems.

Overall, previous studies show a gradual shift, from traditional image processing techniques toward deep learning–based automated solutions for seed classification and quality assessment. While much of the existing literature focuses on multi-class seed variety identification and large scale classification tasks, comparatively fewer works address structured software pipelines specifically tailored for binary seed damage detection. The present work addresses this gap by developing a modular, end-to-end CNN-based software framework optimized for efficient, reliable, and deployment ready seed damage classification.

III. PROPOSED MODEL

The proposed system is designed as an end-to-end software framework for automated seed damage detection using Convolutional Neural Networks (CNN). The architecture follows a structured flow beginning with image acquisition and preprocessing, progressing through hierarchical feature extraction, and concluding with binary classification into Damaged or Undamaged categories.

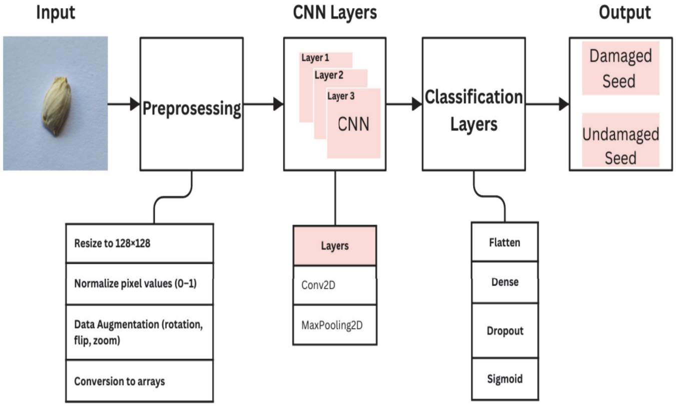


Fig. 1: Proposed System Model Pipeline

A. *Input (as image)*

Seed images serve as the primary input to the system. The dataset is organized into structured training, validation, and testing directories to facilitate supervised learning and systematic evaluation.

B. *Preprocessing Stage*

To ensure consistency and enhance robustness, input images undergo preprocessing operations including:

- Resizing to 128 × 128 resolution
- Pixel normalization to the range [0,1]
- Controlled augmentation (rotation, zoom, shear, width and height shift, and horizontal flip for the training set)

These steps standardize input dimensions and improve the model's ability to generalize across variations in orientation, scale, and illumination.

C. *CNN Based Feature Extraction*

This is the core of the system model. The Convolutional Neural Network automatically extracts visual features that distinguish damaged from undamaged seeds. The CNN model consists of several layers:

1. Convolutional Layers These layers apply multiple learnable filters to the input image. Functions:

- Capture local visual features such as edges, texture patterns, cracks, and surface irregularities.
- Learn increasingly complex features at deeper layers.

2. Activation Layers (ReLU) After each convolution operation, an activation function (typically ReLU) is applied.

Functions:

- Introduces non-linearity.

- Helps the model learn complex relationships between features.
- Prevents vanishing gradient issues.

3. Pooling Layers (Max Pooling) Pooling layers reduce the spatial dimensions of feature maps.

Functions:

- Down-sample information
- Reduce computational complexity
- Retain the most important features

IV. IMPLEMENTATION

This section describes the practical realization of the proposed system, including dataset preparation, model configuration, training procedure, evaluation methodology, and inference workflow.

A. Dataset Preparation

The dataset is organized into two primary directories, namely *Train* and *Test*, which are used for model training and performance evaluation, respectively. Each directory contains two subfolders corresponding to the class labels: *Damaged* and *Undamaged*. This directory structure enables efficient loading and labeling of images during training and testing. Additionally, a validation subset was created from the training data using an 80:20 split to monitor model performance during training and prevent overfitting. Strict separation between training, validation, and test datasets was maintained to prevent data leakage.

All images are resized to a fixed resolution to ensure uniform input dimensions for the convolutional neural network. The dataset is loaded using the `ImageDataGenerator` utility, which facilitates efficient data handling and preprocessing during runtime. Pixel values are normalized by rescaling them to a range of [0, 1], which helps in faster convergence and stable training.

To improve the robustness and generalization capability of the model, data augmentation techniques such as rotation, horizontal flipping, zooming, and shearing are applied exclusively to the training dataset. These transformations help the model learn invariant features and reduce overfitting. The test dataset is not augmented and undergoes only normalization to ensure unbiased performance evaluation.

These preprocessing steps help maintain consistent input data during training, allowing the CNN model to effectively learn discriminative features for accurate classification between damaged and undamaged images.

B. CNN Architecture Implementation

The implemented CNN model consists of:

- Three convolutional blocks with filters (32, 64, 128)
- Two Conv2D layers in each block
- Batch Normalization after convolution layers
- Dropout layers (0.3–0.4) for regularization
- MaxPooling after each convolutional block
- Flatten layer
- Dense layer (64 neurons)
- Dropout (0.6) before output layer
- Output Dense layer (1 neuron, Sigmoid activation)
- L2 regularization applied to convolutional and dense layers

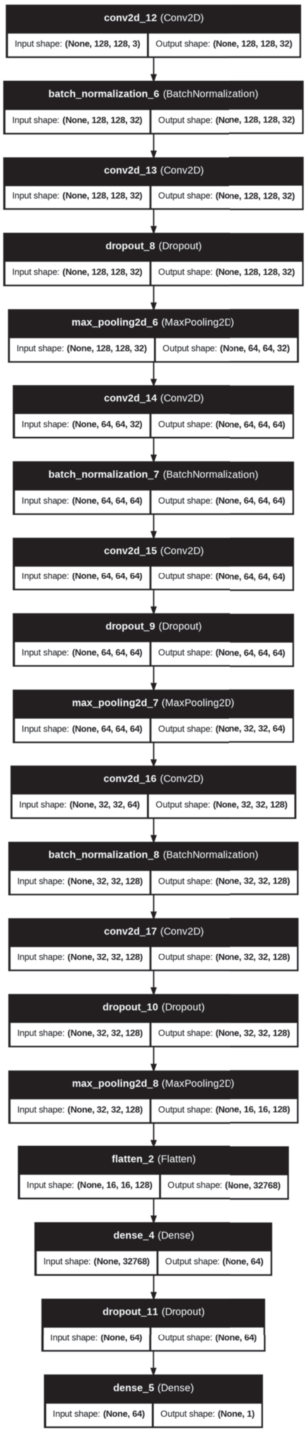


Fig. 2: CNN Layer Architecture with Input and Output Shapes

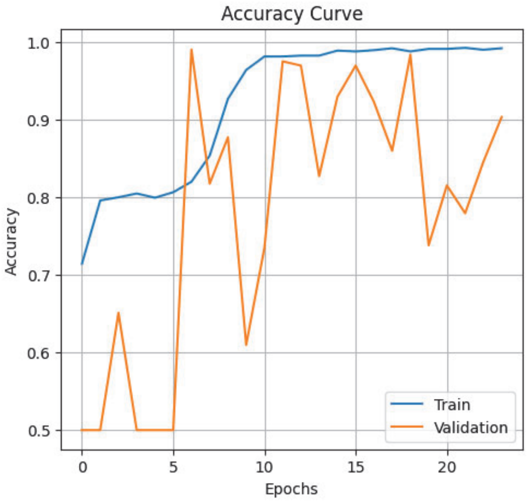
Fig. 2 illustrates the dimensional transformation of feature maps through successive convolution and pooling operations, demonstrating progressive spatial reduction and feature abstraction.

C. Training Configuration

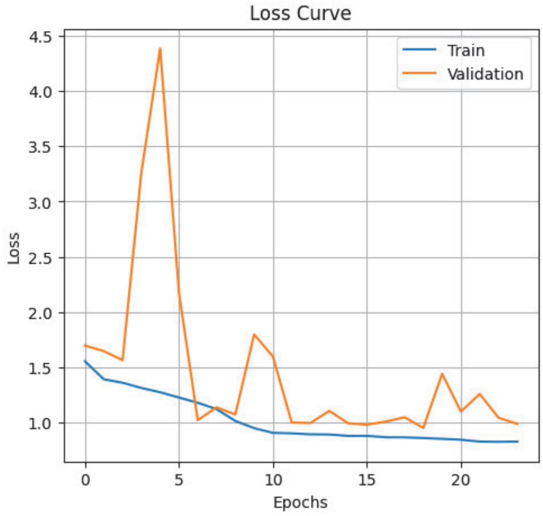
The model was compiled using:

- Optimizer: Adam (learning rate = 8e-5)
- Loss Function: Binary Cross-Entropy
- Evaluation Metric: Accuracy

Training was conducted for up to 25 epochs with early stopping. Learning rate reduction was applied when validation performance plateaued. Performance was monitored using training and validation accuracy and loss curves.



(a) Accuracy



(b) Loss

Fig. 3: Training and Validation Accuracy & Loss Curves

Fig 3 demonstrates overall convergence behavior, with validation performance closely following training performance, showing that the model learns effectively while limiting overfitting.

D. Performance Evaluation

Model performance was evaluated using:

- Confusion Matrix
- Accuracy
- Precision
- Recall
- F1 Score
- Specificity
- ROC–AUC

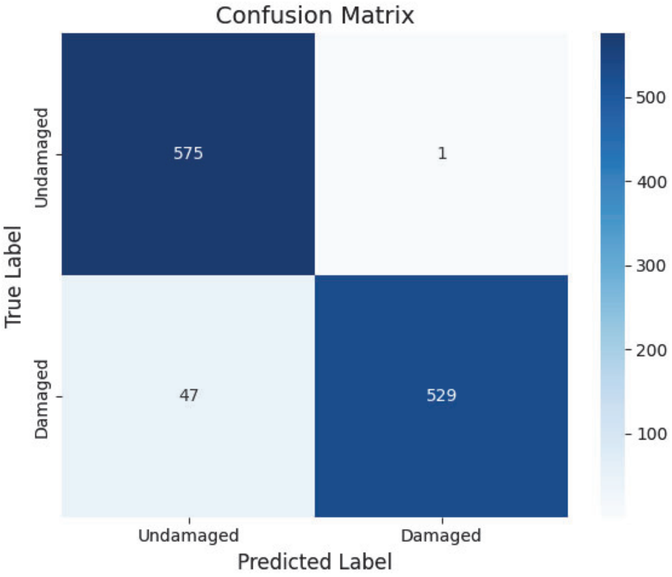
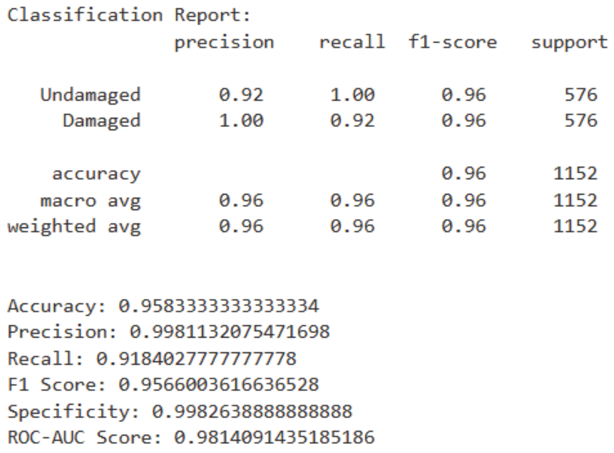


Fig. 4: Confusion Matrix

The confusion matrix indicates good classification performance with low misclassification and only a small number of false negatives during damaged and undamaged seed classification.



```
Classification Report:
               precision    recall  f1-score   support

   Undamaged       0.92      1.00      0.96       576
     Damaged       1.00      0.92      0.96       576

    accuracy                           0.96      1152
   macro avg       0.96      0.96      0.96      1152
weighted avg       0.96      0.96      0.96      1152


Accuracy: 0.9583333333333334
Precision: 0.9981132075471698
Recall: 0.9184027777777778
F1 Score: 0.9566003616636528
Specificity: 0.9982638888888888
ROC-AUC Score: 0.9814091435185186
```

Fig. 5: Performance Metrics Summary

The evaluation results indicate:

- Accuracy ≈ 95.83%

- High precision and recall for both classes
- ROC–AUC ≈ 0.981
  These results confirm the robustness and reliability of the proposed CNN model for binary seed damage detection.

E. Prediction Workflow

For single-image inference, the following steps are executed:

- Upload image
- Convert to RGB format
- Resize to 128 × 128
- Normalize pixel values
- Expand dimensions for model input
- Predict probability
- Assign class label (Damaged / Undamaged)
- Display result with accuracy score

V. RESULTS AND ANALYSIS

To evaluate the effectiveness of the proposed CNN-based seed damage detection system, representative test samples from multiple seed categories were analyzed. The system was tested on both damaged and undamaged seeds across Apple, Bitter Gourd, Custard Apple, and Mosambi varieties. The prediction outputs include the classified label and corresponding accuracy score.

A. Observations

1) High Classification Accuracy: Most predictions produced high accuracy values, demonstrating strong discriminative capability.
2) Robust Performance Across Seed Types: The model maintains consistent performance across different seed varieties, indicating effective feature generalization.
3) Minor Variations in Accuracy: Slightly lower accuracy values in certain cases may be attributed to subtle visual similarities or lighting variations.
4) Correct Binary Classification: Representative samples were successfully classified into Damaged and Undamaged categories.

B. Overall Model Performance

Comprehensive evaluation on the full test dataset yielded:

- Accuracy ≈ 95.83%
- Precision ≈ 0.998
- Recall ≈ 0.918
- F1-Score ≈ 0.956
- Specificity ≈ 0.998
- ROC–AUC ≈ 0.981

VI. CONCLUSION

This work developed an image-based seed damage detection system built around a optimized CNN-based software pipeline. The combination of image preprocessing, compact CNN feature extraction, and lightweight TensorFlow Lite inference enables accurate and reliable classification of seeds as Damaged or Undamaged on resource-constrained embedded platforms without reliance on cloud computing. The system can support reliable and scalable seed quality assessment suitable for agricultural use. Future enhancements may include multi-class damage assessment, cloud-based storage, mobile application integration, and expanded datasets for improved generalization.

Name	*Image*	*Output*
Apple		🧠 Prediction: Undamaged Seed 📊 Confidence: 99.93%
Apple		🧠 Prediction: Damaged Seed 📊 Confidence: 99.76%
Bitter gourd		🧠 Prediction: Undamaged Seed 📊 Confidence: 100.00%
Bitter gourd		🧠 Prediction: Damaged Seed 📊 Accuracy: 100.00%
Custard		🧠 Prediction: Undamaged Seed 📊 Accuracy: 99.70%
Custard		🧠 Prediction: Damaged Seed 📊 Accuracy: 97.24%
Mosambi		🧠 Prediction: Undamaged Seed 📊 Accuracy: 100.00%
Mosambi		🧠 Prediction: Damaged Seed 📊 Accuracy: 100.00%

Fig. 6: Representative Predictive Results

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