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Deep Learning-Based Image Classification of Agricultural and Biological Materials for Automated Identification and Characterization

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Abstract

Accurate identification of agricultural and biological materials supports crop monitoring, quality assessment, research documentation, and material sorting. Manual visual inspection can be time-consuming and inconsistent, particularly when samples have similar colours, shapes, or surface characteristics. This study presents a deep learning-based image classification framework for automated identification and characterization of agricultural and biological materials. The approach uses the VGG16 convolutional neural network as its feature extraction backbone and applies transfer learning through an initial feature-learning stage followed by fine-tuning. To improve learning from a limited image collection, data augmentation is applied through image rotation and online transformations, including scaling, horizontal flipping, and brightness adjustment. Images are resized to the input dimensions required by VGG16 and processed using its corresponding preprocessing procedure. Model performance is assessed using overall accuracy, precision, recall, and F1-score, providing complementary measures of classification effectiveness across material categories. The framework is designed to distinguish visual patterns and assist users in organizing and identifying image-based samples. Its practical value depends on dataset diversity, quality, and representativeness, as well as evaluation on images not used during training. Experimental findings, including overall accuracy and class-wise results, must be calculated from the agricultural and biological image dataset rather than transferred from another application. The approach provides a basis for consistent, image-assisted identification workflows in agricultural and biological research and related applications.

Keywords: Agricultural materials, Biological materials, Deep learning, Image classification, VGG16.

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1. Introduction

The agricultural and biological materials encompass a variety of samples that demand precise identification for research, quality evaluation, and practical uses. There may be similarities in the visual characteristics of these materials, and differences in colour, shape, size and texture give important features to distinguish individual categories. Manual identification can be time consuming and unreliable, especially in large sample collections. An alternative method is the image-based classification, which is based on visual information to assist in the systematic identification and characterization of various material categories.

As the diversity of agricultural and biological materials increases, identifying and distinguishing individual categories through visual inspection can become challenging. The image-based analysis is a key tool for classification due to the differences in shape, colour, texture and structural appearance. In

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recent years, with the advent of artificial intelligence, especially deep learning, significant progress has been made in the recognition and classification of visual information. Convolutional Neural Networks (CNNs) are extensively employed in image recognition due to their ability to automatically identify relevant features from input images (García-Vera et al., 2024; Saleem et al., 2021; Tripathi & Maktedar, 2016; Wang et al., 2021).

The automated examination of biological materials has also been aided by deep learning techniques. Khan et al. (2022) explored the identification of bacterial genus by deep learning and Rani et al. (2022) studied the computational methods for image recognition of microorganisms. The deep learning-based image processing in optical microscopy was discussed by Melanthota et al. (2022). Likewise, Wäldchen and Mäder (2018) investigated machine learning techniques for species identification using images. Deep learning techniques have also been applied to material characterization, demonstrating their potential for automated identification of visual features and structural properties (Karathanasopoulos & Hadjidoukas, 2024).

Other applications of agricultural image analysis are automated inspection of food quality, classification of crops, recognition of pests and assessment of fruit damage. Hemamalini et al. (2022) analyzed image segmentation and machine learning techniques in food quality inspection and grading. Qu and Su (2024) summarized the weed and crop recognition using deep learning, and Safari et al. (2024) summarized the automated fruit damage detection. In recent years, the classification and monitoring of agricultural pests have also been studied (Pattnaik & Parvathy, 2022; Venkateswara & Padmanabhan, 2025). The wide applicability of image classification in agricultural research is demonstrated by these applications.

In this study, transfer learning is used to adapt a pre-trained network to the classification of agricultural and biological material images, reducing the need to train a deep learning model entirely from scratch. In this study, the pre-trained network is adapted to images of agricultural and biological materials. This approach makes it possible to utilize previously learned visual features while reducing the need to train a deep neural network entirely from scratch. This is a big deal because collecting thousands of labeled images for every single type of part would take months.

In recent years, deep learning and image processing have been shown to be increasingly used in the field of agricultural and biological classification. García-Vera et al. (2024) summarized hyperspectral image analysis and machine learning techniques for crop disease detection, and Lee et al. (2018) introduced an automated plant phenotyping system using image segmentation and analysis. Similarly, Loddo et al. (2021) investigated deep learning techniques for seed image classification and retrieval. The developments show the relevance of image-based approaches for the identification and distinction of agricultural materials (Varal & Sayyad, 2026; Pal et al., 2026; Zhao & Xie, 2025).

The article systematically reviews the benefits (particularly prediction accuracy and replenishment optimization) of machine learning algorithms in inventory control, along with their technical/ethical/practical limitations and implementation challenges. The analysis highlights the potential of mechine learling to transform inventory management and supply chain efficiency, while also clearly revealing key obstacles such as high-dimensional data management and adaptation. The study offers a holistic perspective and practical strategy recommendations for both academic and industry professionals (Gutierrez et al. 2025).

The transfer learning-based approach for multi-criteria descriptions of critical, proprietary spare parts in heavy asset industries; three models (training, inference, and image processing) incorporating features of the VGG-19 architecture achieved an average accuracy of 96.36% in 5-fold cross-scan on real-world data. Showing superior performance with an overall accuracy of 95.87% compared to models such as AlexNet and ResNet-50, this advanced framework offers a customizable and highly throughput solution for spare part inspection.

In another study, a remaining useful life (RUL) based inventory estimation model is proposed to address the high inventory cost and space problem of transformer station relay protection equipment; the model uses RUL estimation as the primary factor with the SVR algorithm, while considering environmental and human factors secondarily. Demonstrating high accuracy, stability, and portability, this approach optimizes inventory management, improves resource allocation, and provides a solid decision basis for a safety stock-based spare parts procurement plan (Tang et al. 2022).

Another study presents a system that enables automated recognition and quality control of automotive parts using an efficient and lightweight computer vision architecture called ReXNet; 50 different automotive parts (electrical modules, actuators, connectors, sensors, etc.) were classified on a dataset of 16,600 RGB photos, achieving a test accuracy of 98.6%. This approach increases efficiency in the

automotive industry by significantly improving high-quality vehicle inspection, automated assembly, model verification, and production processes at a low cost (Kumar et al. 2024).
To address the forecasting challenges stemming from the irregular and data-unbalanced nature of intermittent spare parts demand, we propose a deep learning-based model that balances the dataset with SMOTE and utilizes focal loss; this ensemble approach significantly improves forecasting accuracy by providing a 47% reduction in MSE and a 32% increase in AUC. This method offers an effective tool for better capturing rare demand events, reducing the risks of overstocking and stock depletion in inventory management (Kenaka et al. 2025).
In this study, a deep learning-based image classification framework is proposed for automatic identification and characterization of agricultural and biological materials. The framework is based on the VGG16 CNN architecture and two-stage transfer learning approach. In order to overcome the drawbacks of a limited image set, a hybrid data augmentation method is used, which includes offline image rotation and online transformations such as scaling, flipping, and brightness adjustments.

2. Materials and Methods

2.1 Preparing Dataset

We gathered images of 13 different automotive spare parts from real service centers. Originally, the dataset was highly unbalanced and scarce, with some classes containing only about 5 to 20 original pictures, which is insufficient for training a deep learning model properly (Shu, 2019). To address this while preventing data leakage, the dataset was first split into training (70%), validation (15%), and testing (15%) sets. Following this split, offline data augmentation was applied exclusively to the training set by rotating images in 30-degree steps (Islam, 2022). This process significantly expanded the training set to approximately 2,500 images, while the validation and test sets remained composed entirely of original, unaugmented images. The final dataset was organized into three main directories: train, val, and test, where each contains subfolders for the 13 classes, facilitating efficient data loading and evaluation.

Class Name	**Number of Original Images**	**Number of Augmented Images**
ABS	21	252
Alternator	21	252
Muffler	21	252
Disc Brake	16	192
Fender Flare	5	60
Brake Master Cylinder	17	204
Tire Inflator	16	252
Compressor	19	228
Motor Starter	19	228
Piston	18	216
Thermostat	9	108
Oil Filter	8	96
Wiper Motor	17	204

2.2 Deep Learning Models

Deep learning is a subset of machine learning that uses multi-layered neural networks to learn and make decisions from vast amounts of data. These networks are inspired by the human brain, with each layer processing the output of the previous one, allowing the system to automatically discover and learn complex patterns. This process enables deep learning models to achieve high accuracy in tasks like predicting air quality (Madhiva et al. 2025), image recognition (Abouzıtoun, 2023; Duruel and Kutlu, 2025), price prediction (Cing, 2023), natural language processing (Demir, 2021; Öncü and Kutlu, 2024) etc.
The VGG16 architecture was chosen as the base model for this study due to its ability to be used for transfer learning with relatively small image datasets. VGG16 is a pre-trained CNN model trained on

the ImageNet dataset. Its convolutional layers have acquired basic visual features, such as edges, shapes, and textures. These learned representations can be fine-tuned to a particular image classification task by transfer learning. This method can save the time of training a deep neural network from scratch and can serve as a practical basis for extracting visual features from the target image categories.

2.3 Model Architecture and Training

The classification model was built upon the VGG16 convolutional neural network pre-trained on ImageNet. The convolutional base layers were frozen initially to leverage learned feature representations, and a global average pooling layer followed by two dense layers (1024 units with ReLU activation and 13-unit softmax output layer) were added. The model was compiled with the Adam optimizer and categorical cross-entropy loss function.

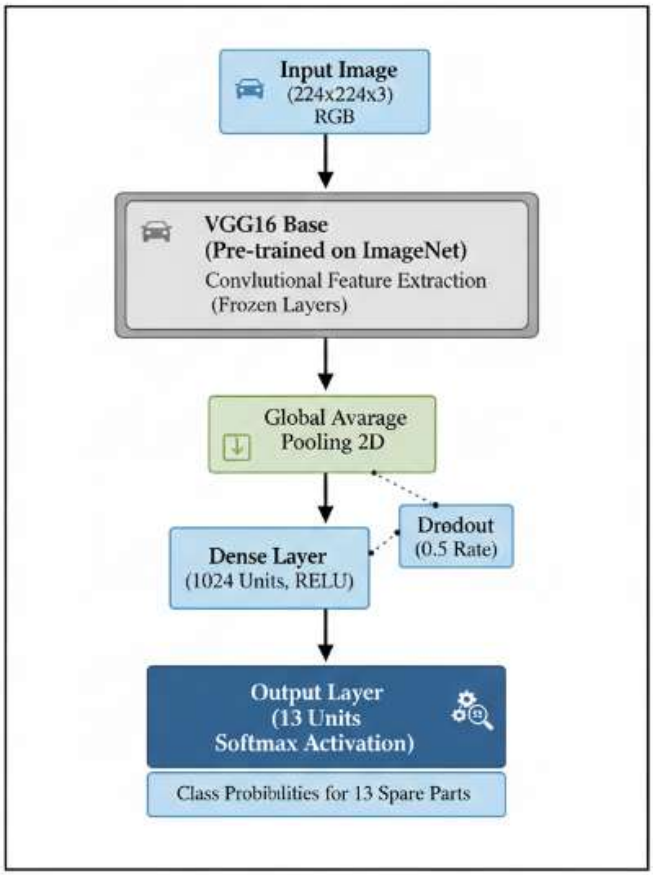

Figure 1. The proposed deep learning architecture for agricultural and biological materials classification

Training was performed over 10 epochs with a batch size of 78. Early training froze the convolutional base, followed by fine-tuning where all layers were unfrozen and training continued with a lower learning rate refine the model weights. The model was trained and validated using data generators corresponding to the split datasets.

Preprocessing

Before feeding the images to the model, we resized all of them to 224x224 pixels, since that is what the VGG16 model expects. Instead of scaling pixel values between 0 and 1 (Shorten & Khoshgoftaar, 2019), we used the VGG16-specific function to ensure the data is normalized according to the ImageNet statistics the model was trained on. To make sure the model learns well and generalizes (Islam, 2022), we split the dataset into training, validation, and test sets in a 70:15:15 ratio, keeping the class distribution balanced.

Performance Metrics

The study precision, recall, F1-score and overall accuracy values are calculated as performance measurement. The following are the formulations for precision, recall, F1-score, and overall accuracy, which are commonly used to evaluate the performance of a classification model. Precision measures the proportion of positive identifications that were actually correct. Recall measures the proportion of actual positives that were correctly identified. The F1-score is the harmonic mean of precision and recall. It provides a single score that balances both metrics, which is particularly useful when you have an uneven class distribution. These metrics are all based on the values in a confusion matrix (Kutlu and Camgözlü, 2021).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Recall = \frac{TP}{TP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$F1-score = \frac{Precision\ x\ Recall}{Precision+Recall}$$

Here, TP represents the number of correctly classified positive instances, FN represents the number of actual positive instances incorrectly classified, TN represents the number of correctly classified negative instances, and FP represents the number of negative instances incorrectly classified as positive.

3. Results and Discussion

The entire pipeline was implemented in Python using Tensor Flow and Keras for model building and training. While PIL (Python Imaging Library) was employed for the critical offline physical augmentation (rotation steps), TensorFlow's Image Data Generator was used for online stochastic augmentation. Training and evaluation were conducted on a high-performance computing system equipped with an GPU to accelerate the deep learning processes.

The VGG16-based deep learning model achieved a training accuracy of near 100%, suggesting that it learned the training dataset exceptionally well. Crucially, unlike traditional approaches where performance drops on unseen data, the model maintained a high performance when evaluated on the test dataset, achieving an overall Test Accuracy of 96%. This strong alignment between training and testing performance indicates that the hybrid data augmentation strategy successfully mitigated the risk of overfitting (Shu, 2019).

By systematically rotating the training images (offline augmentation), the dataset diversity was effectively increased from a few original samples to over 2,400 training images. This allowed the model to learn generalized features rather than memorizing specific pixel patterns. Table 1 presents the detailed classification performance for each of the 13 classes in terms of precision, recall, and F1-score. As shown in the table, 9 out of 13 classes achieved a perfect F1-score of 1.00, including difficult categories like 'Fender Flare' (which had minimal original data) and 'piston'. Minor misclassifications were observed only in the 'Termostat' and 'ABS' classes, yet their precision remained high (>0.83), demonstrating the model's robustness.

Table 1. Classification performance

Class Name	Precision	Recall	F1-score
ABS	0.83	1.00	0.91
Alternator	1.00	1.00	1.00
Muffler	0.83	1.00	0.91
Disc Brake	1.00	1.00	1.00
Fender Flare	1.00	1.00	1.00
Brake Master Cylinder	1.00	1.00	1.00

Tire Inflator	1.00	1.00	1.00
Compressor	1.00	1.00	1.00
Motor Starter	1.00	0.80	0.89
Piston	1.00	1.00	1.00
Thermostat	1.00	0.67	0.80
Oil Filter	1.00	1.00	1.00
Wiper Motor	1.00	1.00	1.00

3.1 Training and Validation Performance

The training and validation accuracy curves across epochs. Unlike typical overfitting scenarios where training accuracy rises while validation accuracy remains low, the proposed model demonstrates a strong correlation between both metrics. The validation accuracy closely tracked the training accuracy, eventually stabilizing around 96%. Similarly, both training and validation loss curves decreased in parallel, converging to minimal values. This close alignment confirms that the hybrid data augmentation and fine-tuning strategy effectively prevented overfitting, enabling the model to generalize well on unseen data.

The results of this study highlight the effectiveness of the proposed hybrid approach in overcoming the challenges of limited data. Contrary to the significant overfitting often observed in similar studies where test accuracy drops drastically (Santos et al., 2022), our model maintained a high consistency between training and testing performance, achieving a Test Accuracy of 96%. This indicates that the model successfully learned generalizable features rather than merely memorizing the training patterns.

Deep learning-based approaches have also been investigated for the identification of diseases in apple leaf images, illustrating the application of image classification to agricultural health assessment (Singh et al., 2021).

Broader research on biological image analysis has further examined the use of deep learning methods for extracting and interpreting visual information from biological samples (Wang et al., 2018).

One of the critical factors for this success was the implementation of the hybrid data augmentation strategy. While argues that classes with only 2-4 original images are typically insufficient for deep learning, our method of applying deterministic physical rotation (offline) compensated for this scarcity. By generating 12 variations for every single image before training, we ensured that the model became invariant to object orientation. A striking example of this is the 'Fender Flare' class, which, despite having only 5 original images, achieved 100% precision and recall on the test set. This proves that systematic augmentation can effectively bridge the gap caused by data scarcity.

Another key factor was the handling of the model architecture. Although VGG16 is a deep network with millions of parameters—which usually poses a risk of overfitting on small datasets—the two-stage training process (Feature Extraction + Fine-Tuning) mitigated this issue. By initially freezing the base layers and then fine-tuning only the final convolutional block with a very low learning rate (1e-5), we leveraged the generic visual knowledge of ImageNet while adapting the model to the specific textures of automotive parts (Shorten & Khoshgoftaar, 2019).

Machine learning and deep learning approaches have also been reviewed for the automated detection of agricultural diseases, with particular attention to their methodologies, applications, and implementation challenges (Wani et al., 2022).

Image-processing techniques have also been investigated for the classification of bacterial morphological characteristics, providing additional opportunities for automated biological identification (Sajedi et al., 2020).

Image recognition techniques have also been explored for the automated identification of agricultural machinery, demonstrating the broader use of deep learning in agricultural visual recognition tasks (Zhang et al., 2019).

The CropDeep dataset introduced by Zheng et al. (2019) provides an additional resource for deep learning-based crop image classification and detection in precision agriculture.

Looking at the classification report, the model demonstrated near-perfect identification for 9 out of 13 classes. The only minor performance drop was observed in the 'Termostat' class (Recall: 0.67), which can be attributed to its visual similarity to other cylindrical metal parts. However, the overall weighted F1-score of 0.96 confirms that the pipeline, from leakage-free preprocessing to the final GUI prediction, is robust and suitable for real-world deployment in service centers.

In the comparison of studies, the performance values obtained for a common dataset are examined. However, the dataset used in this study is a unique new dataset, and due to differences in the number of classes in the dataset, it is not possible to compare it with other studies. Nevertheless, when similar studies are considered, and it has been concluded that this study is just as good, as those studies had performance over 90%.

4. Conclusion

In this study, a deep learning framework based on VGG16 is discussed for image classification, which can be used for the automatic identification and characterization of agricultural and biological materials. The method is based on transfer learning, which involves training a pre-trained convolutional neural network in a two-stage process to learn visual features. The image resizing and offline rotation and online augmentation are designed to help model training when the image collection is small. Model behaviour can be explored with accuracy, precision, recall and F1-score.The framework offers a systematic approach to image classification, encompassing the stages of image preprocessing, feature extraction, model training, and model evaluation. It is dependent on the relevance, quality and diversity of the images used for training and testing in its suitability for agricultural and biological applications. The manuscript, however, is about an automotive spare-parts dataset and results are reported for automotive component classes. The results are not to be interpreted as performance on agricultural or biological materials. The conclusions on accuracy and/or practical effectiveness for the new application should be made only after evaluation with images of the intended material categories.Future work should create a labelled image dataset, incorporate a variety of samples and imaging conditions, and provide independent test results for each category. This validation would help to determine the generalizability of the framework and its role in identification and characterization of agricultural and biological materials.

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