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# OPTIMISING SOYBEAN SEED CLASSIFICATION THROUGH ENSEMBLE DEEP LEARNING: A NOVEL COMPUTATIONAL APPROACH

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## ABSTRACT

**Purpose:** This research presents a framework based on convolutional neural networks (CNNs) for automatically classifying soybean seeds into five categories: intact, spotted, immature, broken, and damaged.
**Design/Methodology/Approach:** The framework includes nine pre-trained CNN models, including DenseNet(169,121,201), InceptionV3, MobileNetV2, ResNet50V2, VGG (16,19), and Xception, which were evaluated and compared in terms of accuracy, recall, precision, and F1 parameter using the dataset. Data augmentation was used to improve the model's performance and prevent overlearning. An ensemble learning approach using majority voting (MV) was applied to improve the model's generalisation.
**Research Limitation:** The controlled imaging setting limits its generalisability to the real world. But the presented method is definitely one of the best options for evaluating soybean seed quality.
**Findings:** The DenseNet201 and DenseNet169 models showed superiority over the DenseNet201 and DenseNet169 models due to their superior ability to extract features and share parameters efficiently. These results confirm the effectiveness of deep modelling and group model integration techniques in improving classification reliability and reducing over-allocation. It outperforms all individual models, achieving 98.22% accuracy and 97.68% test accuracy.
**Practical Implication:** Adopting artificial intelligence (AI) technologies offers an effective solution to enhance agricultural productivity and improve seed sorting and quality assessment.
**Social Implication:** Reduced computational demand means lower energy consumption per classification event. At the scale of a full harvest season, this represents a meaningful reduction in the digital carbon footprint of precision agriculture.
Originality / Value: These models, which feature a densely interconnected structure, not only facilitate more efficient feature reuse but also help prevent diminishing gradients.

***Keywords:*** *Convolutional Neural Networks. deep learning. ensemble learning model. precision. soybeans*

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## INTRODUCTION

Soybeans are a versatile legume grown worldwide. It has a good nutritional profile and a wide range of applications in human and animal diets. It accounts for approx. So, 47% of the total cropped areas on the earth (Wei et al., 2020; Pereira et al., 2018).

Global soybean production reached 348.9 million tons in 2017, of which 152.4 million tons were exported by international shipping. With its high protein content, soybeans are a major source of plant protein and are frequently used as a substitute for meat, especially in vegetarian and vegan diets (Behailu et al., 2020).

Soybeans are also packed with vitamins, minerals and antioxidants, all of which are good for your health. Besides human nutrition, soybeans play a major role in animal nutrition. They are one of the main protein sources in livestock feeding (Zhu et al., 2021). Besides that, soybean oil, extracted from soybean seeds, is widely used in the food industry. Not only is it a key ingredient in products such as margarine, mayonnaise, and salad dressings, but it also provides a renewable raw material source for fuel manufacturing, mitigating sustainable energy development, besides the food industry (Hussien et al., 2026).

Initially, mechanical vibrating sieve systems were implemented to detect bad or broken seeds, while manual visual screening relied on characteristics like size, shape, colour, and texture for selecting seeds (Fan et al., 2025). Nevertheless, sieve-based methods might physically damage seeds, and visual assessment is highly subjective, prone to human error, and may not be accurate or consistent. Therefore, the demand for advanced, more reliable, and less damaging methods of seed quality testing is increasing. Over the recent years, the integration of image processing and AI technology has emerged as a promising approach for revitalising agriculture, particularly in seed sorting and quality checking (Sable et al., 2024).

## RELATED WORKS

Yurdakul and Tademir (2023) conducted research to categorise soybean seeds into 5 distinct categories: broken, immature, intact, damaged skin, and defective. For the research methodology, they decided to compare Convolutional Neural Networks (CNNs) with vision transformers (ViT) models. The scientific team worked with soybean seed images and used data augmentation methods to improve the dataset's generalisability.

Seven CNN models pre-trained on ImageNet have been selected for transfer learning and fine-tuning on the target dataset to perform sample classification. The performance of these models was compared using accuracy, recall, and F1 scores. Among the tested models/approaches, the final system achieved an accuracy of 96.02%, confirming its excellent performance and effectiveness in classifying soybean seeds. This study highlights the effectiveness of CNNs for excellent classification, promoting the use

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of AI in agriculture to ensure crop quality, and evaluates various pre-trained models. However, the insufficient size of the original dataset, the possibility that high performance is limited to this particular dataset, and the failure to generalise the proposed system to other datasets to increase its reliability are among the limitations of this study (Yurdakul & Taşdemir, 2023).

Wendling et al. (2024) focused on sorting soybean seeds based on quality by developing rapid, non-destructive methods for seed quality assessment, thereby eliminating the need for traditional, time-consuming, and labour-intensive physical and chemical testing. Wendling et al. (2024) proposed a novel approach using near-infrared (NIR) spectroscopy to obtain information from healthy and diseased soybean seeds.

Wendling et al. (2024) also employed signal processing techniques to detect unique spectral characteristics. Subsequently, ML algorithms, such as Support Vector Machine (SVM), Random Forest (RF), and Partial Least Squares Discriminant Analysis (PLS-DA), were trained to sort the seeds based on their characteristics. Machine learning algorithms combined with NIR technology demonstrated that it is easier to separate healthy and diseased seedlings. The best-performing algorithm was RF, with an accuracy of about 98%. This work offers the opportunity to evaluate seed quality using a privacy-protecting, non-destructive method at low cost and with minimal time commitment, making it a very worthwhile approach for agricultural field quality control.

Despite achieving high accuracy, the proposed approach relies heavily on the quality of NIR signals; therefore, any noise or measurement error directly affects the results. Furthermore, the system lacks validation on large and diverse datasets, limiting its generalizability and robustness in a real-world agricultural environment (Wendling et al., 2024).

Li et al. (2021) noted that traditional chemical and physical analysis methods are commonly used for soybean seed classification, but these methods rely heavily on chemicals, generate waste, and require multiple complex steps. They used convolutional neural networks (CNNs) and laser-induced breakdown spectroscopy (LIBS) to differentiate between 10 different soybean seed samples. Three spectra were taken from each seed, and a spectral array was created by combining the different spectra, which were subsequently fed into the neural network. Their 2D-PCSA-ResNet model obtained a test classification accuracy of 91.75%, surpassing other methods such as SVM. The spectral acquisition required less than 30 seconds per seed (Li et al., 2021). This research provides a rapid, non-destructive, and environmentally friendly approach to accurately identify soybean varieties and leverages deep learning methods on spectroscopic data to improve classification performance. Like any method, it has its limitations, one of them being that some genetically close species, such as Hedou 33 and Hedou 25, have shown taxonomic overlapping, and therefore, the method still requires further development for its field use with portable LIBS devices and increasing the diversity of experimental samples (Li et al., 2021).

Matera et al. (2025) conducted research to address the reduction in a standardised method for assessing soybean seed viability after storage. They created a dependable viability classification system through the Accelerated Aging (AA) test at 41 C for 24 h. The research involved analysing 15 samples of five

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soybean varieties stored for 6 months, along with various physiological tests, including germination percentage, field germination percentage, number of initially germinated seeds, seedling viability assessment, and electrical conductivity. Data validated the test's suitability for determining seed viability and field germination potential, with strong correlations (R > 0.80). Matera et al. (2025) proposed a classification system with several categories: very high (90–100%), high (80–89%), medium (61–79%), and low (≤60%). A key benefit of this research is that it's a practical, non-destructive, and standardised classification system for monitoring seed quality. Its disadvantages include reliance on a small sample size and specific storage conditions, which limit the generalizability of its results across diverse temporal and climatic environments. (Matera et al., 2025).

Rybacki et al. (2025) conducted a study using an applied experimental approach and a Revo Point Range 3D scanner to build an intelligent digital model for sorting and evaluating the quality of five different soybean varieties using 3D imaging techniques, including 3D CNNs. The proposed model achieved 95.54% accuracy in the training phase, also 90.74% in the validation phase. Sorting each seed took between 5.54 and 8.78 milliseconds, with a total error of 0.0992. A key feature of this study is its use of AI and 3D imaging techniques to achieve accurate, rapid classification. However, the study's limitations include its focus on a small number of varieties and its requirement for advanced computing power and a controlled experimental environment, which may restrict its practical application in the field (Rybacki et al., 2025).

Sable et al. (2024) conducted a pilot study using DL algorithms to classify and identify defects in soybean seeds. With the assistance of agricultural specialists in the Maritjapur region of India, 1000 seeds were collected and classified into two main categories (healthy and damaged) and seven defect subcategories (broken, cracked, damaged, insect-infested, green, purple, and wrinkled). The photos were taken with a Nikon D800 camera under controlled lighting conditions and then enhanced using the Seed Contour Detection (SCD) technique to better visualise the image and precisely identify seed edges. For seed categorisation, a lightweight CNN model, SSDINet, was employed, incorporating DSep-conv and SENet components. The suggested model achieved an accuracy of 98.64% in classification, a significant improvement over traditional models such as SVM (91.89%) and a regular CNN (93.69%). Besides, one of the main benefits of this work is its image classification speed of 4.70 milliseconds. On the other hand, the study limitations were a small number of samples and dependency on the laboratory imaging environment and advanced computer equipment, which can limit the possibility of application in agricultural fields (Sable et al., 2024).

Yang et al. (2024) classified soybean seeds; this study presented an experimental method using deep learning (DL) algorithms to convert spectral images to RGB images. Seven soybean seed varieties were examined using a Resonon hyperspectral imager with a spectral range of 400–1000 nm. The images were then processed by segmenting them to facilitate the identification of each seed. Data enhancement techniques were used to expand the range by rotating and refining images, thereby increasing training set diversity, resulting in a training set of 7616 samples. Seven convolutional neural network (CNN) models were trained: ResNet34, ResNet50, ResNet18, ResNet101, CBAM-ResNet34, SENet-ResNet34, and SENet-ResNet34-DCN. Results showed that the SENet-ResNet34-DCN model achieved the highest classification accuracy (94.24%), surpassing the other models (ResNet34:

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91.75%, ResNet18: 72.25%, CBAM-ResNet34: 92.28%). It also had the lowest training loss (≈0.3) and the fastest execution time (0.0036 seconds per image). Results also revealed that converting spectral photos to RGB increased classification accuracy from 88.87% to 91.75%. This was because the data's colour and texture clarity improved. The study utilised a combination of spectral imaging techniques and attention algorithms to enhance classification efficiency, accuracy, and speed, while constrained to a small sample of taxa and operating in a laboratory imaging setting, necessitating advanced computing equipment (Yang et al., 2024).

Gadotti et al. (2022) used machine learning to sort soybean seed batches based on their physiological quality. The goal was to speed up the evaluation process and reduce mistakes made by people. The study included 65 batches of three soybean varieties, assessed immediately after harvest and after 6 months of storage at 13°C and 60% humidity. Methods used different physiological tests, such as germination, accelerated senescence, tetrazolium seedling emergence in sand, and 1000-seed weight, and they generated a data matrix with 93 rows and 42 columns. Gadotti et al. (2022) used the Random Forest, MLP, and J48 algorithms in WEKA 3.8.5, with 10-fold cross-validation and a Resample filter to achieve class balance. ANOVA and Tukey's test at the 5% significance level were used to assess the system's efficiency by comparing precision, recall, F-measure, and AUC. Results demonstrated that Random Forest not only produced the best overall accuracy of 92.6% but also a good balance between precision and recall. However, MLP was the least successful in classifying intermediate-class data. The study showed that a high natural germination percentage and results from aging and tetrazolium tests were the two major factors influencing seed quality. The use of a comprehensive approach led to the study achieving high accuracy (over 90%). One limitation of the study is that it was done on only one species and a small number of samples, which means its findings cannot be generalised to other crops without further research (Gadotti et al., 2021).

## MATERIALS AND METHOD

This section thoroughly explains the materials and methods used in the present research. Initially, we used a publicly accessible dataset. To improve the model's ability to handle new data, we applied data augmentation with rotation, translation, shear, and zoom transformations. In the experiments, we tested multiple pre-trained CNN architectures, including DenseNet, Inception, MobileNet, ResNet, VGG, and Xception. The characteristics of the best-performing model, including high accuracy and generalisation ability, were combined for soybean seed classification. Figure 1 illustrates the schematic diagram of the proposed study.

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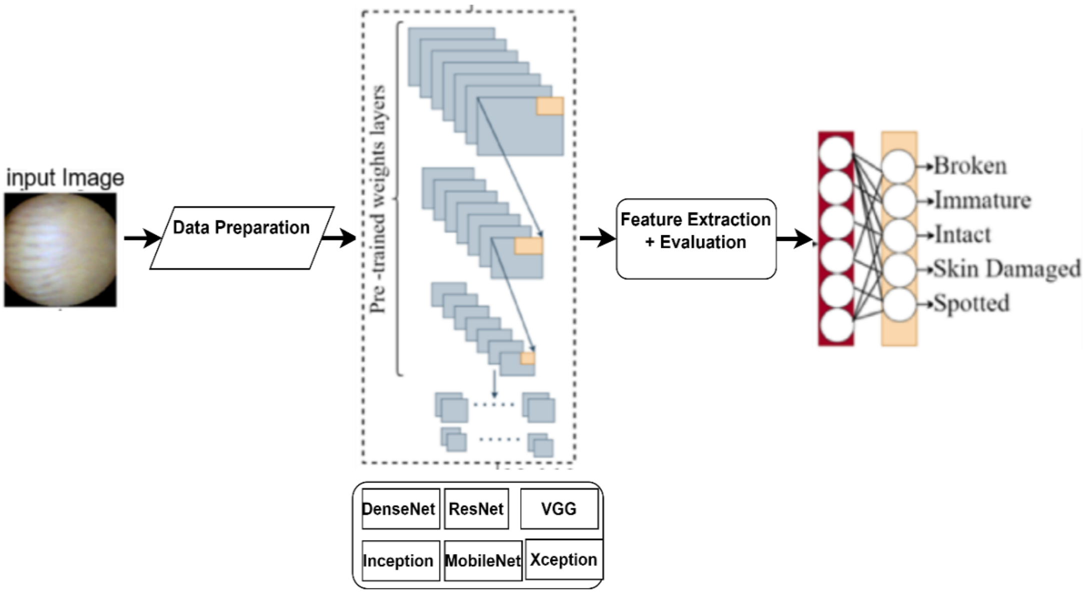


*Figure 1: Schematic Diagram of the proposed study*

**Dataset Description**

The dataset comprises 5,513 photos of five types of individual soybean seed images: intact, spotted, immature, broken, and shell-damaged. There are also more than 1,000 pictures of soybean seeds in each group. The soybean classification standard (GB1352-2009) puts these individual soybean seed pictures into five groups. An industrial camera captured images of the soybeans, which appear to have the seeds touching each other to the naked eye. An image processing technique with segmentation accuracy above 98% subsequently separated individual soybean images (227 × 227 pixels) from the larger soybean images (3,072 × 2,048 pixels). This information is utilised for the examination of soybean seed classification or quality evaluation. Figure 2 shows sample photos for each group quality evaluation. Soybean seed classification or quality evaluation. Quality evaluation. Figure 2 shows sample photos for each group. Soybean seed classification or quality evaluation.

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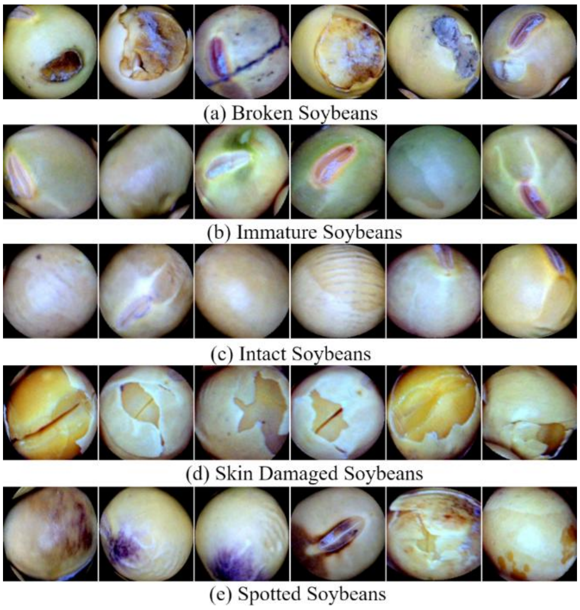


*Figure 2: Sample soybean images from the dataset (Hussien et al., 2026)*

**Data Preparation**

Data preparation is a crucial phase in deep learning projects, as it ensures data is ready for model utilisation. The primary objective of data preparation is to enhance data quality and minimise potential errors during training. Figure 3 illustrates the typical stages of the data preparation process.

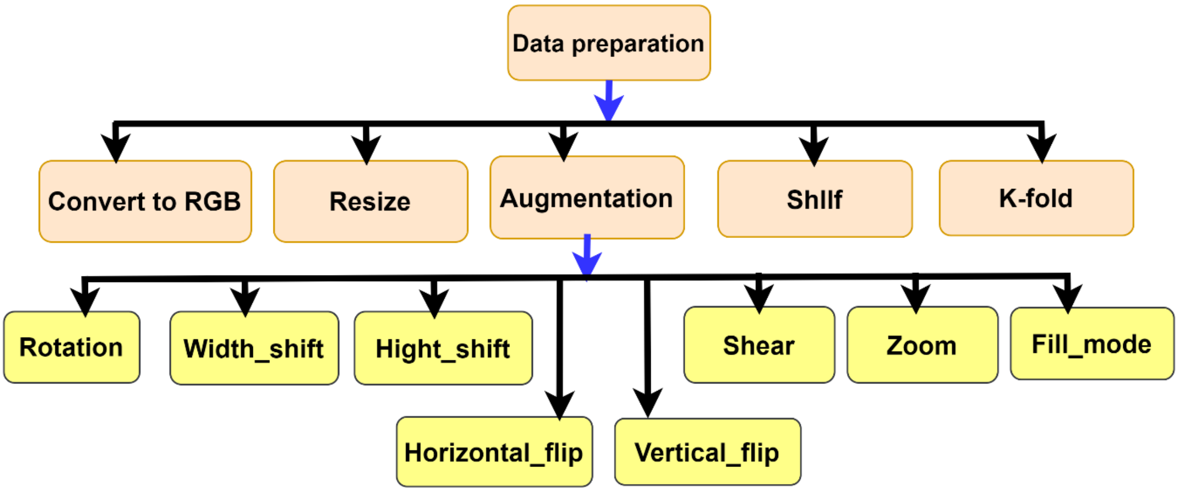


*Figure 3: Data preparation stages (Hussein & Nemer, 2025)*

The data was separated into two parts. The first part, 10%, was used for testing (unseen data), while the remaining 90% was used for training and validation, as shown in Figure 4. Cross-validation

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techniques were applied to divide the data into five groups: each group received 20% of the data from the second part for validation, while the remaining groups were used for training.

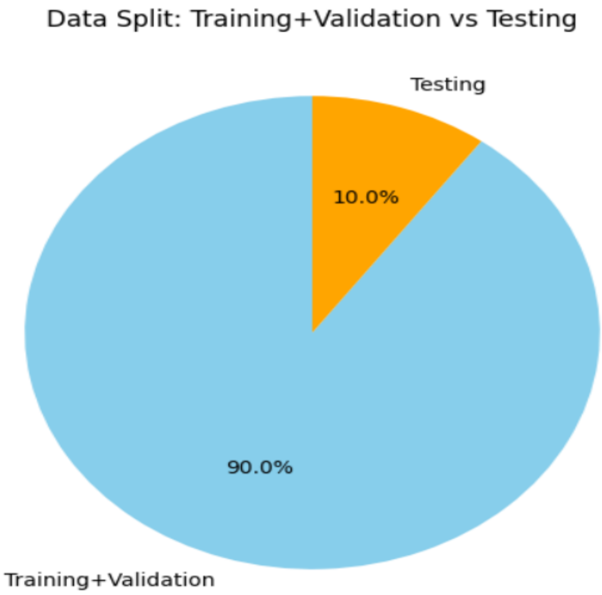


*Figure 4: Split data into training + validation and test sets*

**Convolutional Neural Networks (CNNs)**

CNNs have demonstrated exceptional performance in image classification, recognition, and object detection. They are among the most prominent (DL) algorithms inspired by the mammalian visual cortex (Gbedawo et al., 2024). They have proven highly efficient in image analysis, classification, and object recognition, making them suitable for a range of applications, including image-based seed classification (Hussein & Nemer, 2025). CNN architecture typically consists of an input layer, convolutional layers, pooling layers, a fully connected layer, and an output layer. The convolutional layer extracts distinct features from images using kernels to generate feature maps, while the pooling layer reduces the size of these maps to reduce computational complexity. Image classification using functions such as SoftMax relies on fully connected layers (Hussien & Nemer, 2025). These designs handle changes in space, distortion, and changes in scale well. They also show slight differences in colour, light, and texture. The modular network design minimises errors and accelerates training, even with relatively small datasets. However, the effectiveness of these networks is heavily dependent on data quality. High-resolution images play a critical role in achieving accurate classification. However, challenges exist in making these models perform well across different datasets and in making their decisions understandable. Therefore, future research should focus on improving data quality and on designing easily understandable AI methods to enhance the reliability and effectiveness of these models in real-world scenarios (Tiryaki et al., 2024).

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**Evaluation Metrics**

In the context of soybean image classification, traditional assessment instruments and measures serve as the foundation for evaluating a real-world application model. Using various assessment standards and methods, one can gauge the accuracy, stability, and performance of these models. The main metrics and methods used for the evaluation of soybean image classification algorithms are elaborated on in the following passages (Khalaf et al.,2025).

1) Accuracy is one of the fundamental metrics that can be used to assess performance. It can be applied in a wide range of areas, for example, when classifying images of soybeans. It represents the fraction of correct predictions among all the samples [Eq. (1)] (Nagaraj et al., 2019).

$$\text{Accuracy} = TP + TN/TP + TN + FP + FN \quad (1)$$

where TP stands for true positives, i.e., accurately identified positives; TN stands for true negatives, i.e., accurately identified negatives; FP stands for false positives, i.e., inaccurately identified positives, which is a Type I error; and FN stands for false negatives, i.e., inaccurately identified negatives, which is a Type II error (Amir et al., 2024)

2) Precision quantifies the ratio of accurate positive identifications to the total positive matches identified, as expressed in [Eq. (2)] (Hussien & Nemer, 2025).

$$\text{Precision} = TP/TP + FP \quad (2)$$

3) Recall encompasses the evaluation of the proportion of accurately identified positive matches relative to the total number of positive matches detected [Eq. (3)](Hussien & Nemer, 2025).

$$\text{Recall} = TP/TP + FN \quad (3)$$

4) F1-Score: The precision with recall integration is a very important evaluation. This statistic assesses all facets of the soybean image classification model's performance, encompassing false negatives and false positives. The F1 score is especially beneficial for imbalanced datasets, as it provides a comprehensive evaluation of model performance. F1 score is a more reliable measure of a model's performance than accuracy, which may overlook certain types of errors. This is due to its consideration of both error categories. The F1-score is calculated using Equation (4) (Kim, & Park, 2025).

$$\text{F1-Score} = 2 \times \text{Precision} \times \text{Recall}/\text{Precision} + \text{Recall} \quad (4)$$

5) Confusion Matrix: A confusion matrix encapsulates the model's predictions associated with the actual labels, including accurate forecasts, erroneous predictions, and false predictions. It can be used to pinpoint concern areas and establish various evaluation criteria (Sathyanarayanan, 2024).

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## Ensemble Learning

Ensemble learning is an essential technique in deep learning. Ensemble learning has recently attracted considerable interest in AI, pattern recognition, NNs and data mining. Ensemble learning has demonstrated efficacy and practicality across diverse problem domains and substantial real-world applications. Ensemble learning produces many classifiers or a collection of base learners and integrates their outputs to reduce total variance (Hussein & Nemer, 2025). The integration of many classifiers or base learners significantly improves accuracy relative to a single classifier or base learner (Fan et al., 2025). Voting classification is one of the most powerful ensemble techniques. It combines predictions from multiple underlying models to reach a final decision in a classification problem. It is a common technique in deep learning, where the results of multiple individual classification models are combined to produce a more accurate final decision. There are two types of voting classifiers: Majority voting and soft voting (Hussein & Nemer, 2025). In this research, Majority voting was applied; see Figure 5.

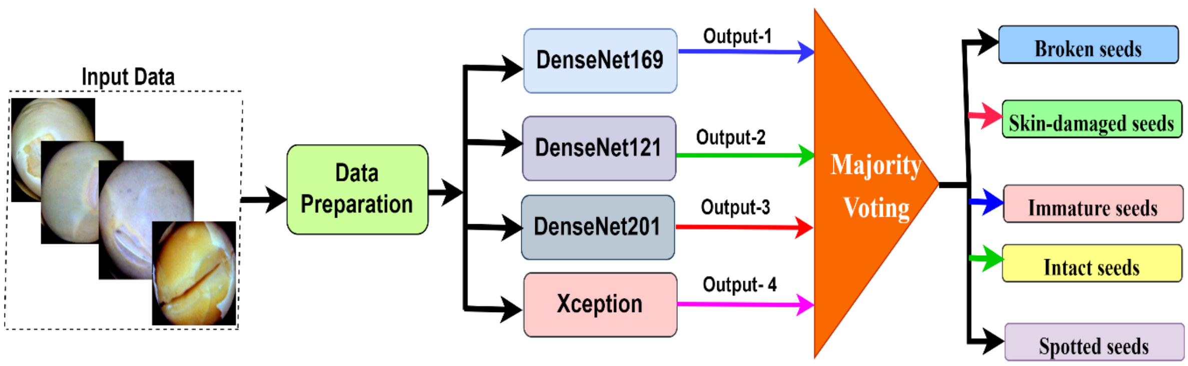


*Figure 5: Majority voting approach for classification of soybean images*

## EXPERIMENTAL RESULTS

In this study, the performance of different CNN models in classifying soybean images is compared. Model performance is evaluated using key classification metrics, including accuracy, precision, recall, and F1 score. Results demonstrate how different model architectures perform in soybean classification. Table1 shows classification performance of nine models (DenseNet201, DenseNet169, DenseNet201, V2 ResNet50, VGG16, VGG19, Inception V3, Xception, and MobileNetV2). Majority voting was applied to the top-performing models (DenseNet169, DenseNet201, and Xception), achieving better results than the individual models.

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*Table 1: Results of models*

| Models | Test accuracy | Validation accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Dense Net169 | 89.52 | 89.35 | 0.89 | 0.89 | 0.89 |
| Dense Net121 | 87.69 | 87.57 | 0.88 | 0.88 | 0.88 |
| Dense Net201 | 90.68 | 89.01 | 0.89 | 0.89 | 0.89 |
| ResNet50V2 | 83.19 | 83.88 | 0.84 | 0.84 | 0.84 |
| VGG16 | 85.19 | 84.9 | 0.85 | 0.85 | 0.85 |
| VGG19 | 82.2 | 82.18 | 0.82 | 0.82 | 0.82 |
| Inception V3 | 81.86 | 81.07 | 0.81 | 0.81 | 0.81 |
| Mobile Net V2 | 83.69 | 84.94 | 0.85 | 0.85 | 0.85 |
| Xception | 86.69 | 83.7 | 0.84 | 0.84 | 0.84 |
| M.V. | 97.68 | 98.22 | 0.9824 | 0.9823 | 0.9822 |

Table 2 shows the values of the parameters used in all models.

*Table 2: Parameters of models*

| Models | K-folds | Dropout | Epoch | Batch size | L. R. | Dense L. |
|---|---|---|---|---|---|---|
| Dense Net169 | 5 | 0.7 | 20 | 16 | 0.00001 | 256 |
| Dense Net121 | 5 | 0.7 | 20 | 32 | 0.00001 | 256 |
| Dense Net201 | 5 | 0.6 | 20 | 32 | 0.00001 | 128 |
| ResNet50V2 | 5 | 0.7 | 30 | 64 | 0.0001 | 256 |
| VGG16 | 5 | 0.5 | 50 | 32 | 0.00001 | 256 |
| VGG19 | 5 | 0.6 | 50 | 32 | 0.00001 | 256 |
| Inception V3 | 5 | 0.7 | 30 | 16 | 0.00001 | 256 |
| Mobile Net V2 | 5 | 0.7 | 30 | 16 | 0.00001 | 128 |
| Xception | 5 | 0.7 | 30 | 16 | 0.00001 | 128 |
| M.V. | 5 | 0.6 | 10 | 32 | 0.00001 | 256 |

Figures (6, 7, 8, 9 and 10) show the confusion matrix, training and validation accuracy plot, and training and validation loss plot for models to which the majority voting technique was applied, in addition to the majority voting model, which shows the difference in performance and efficiency compared to the performance and efficiency of the individual models.

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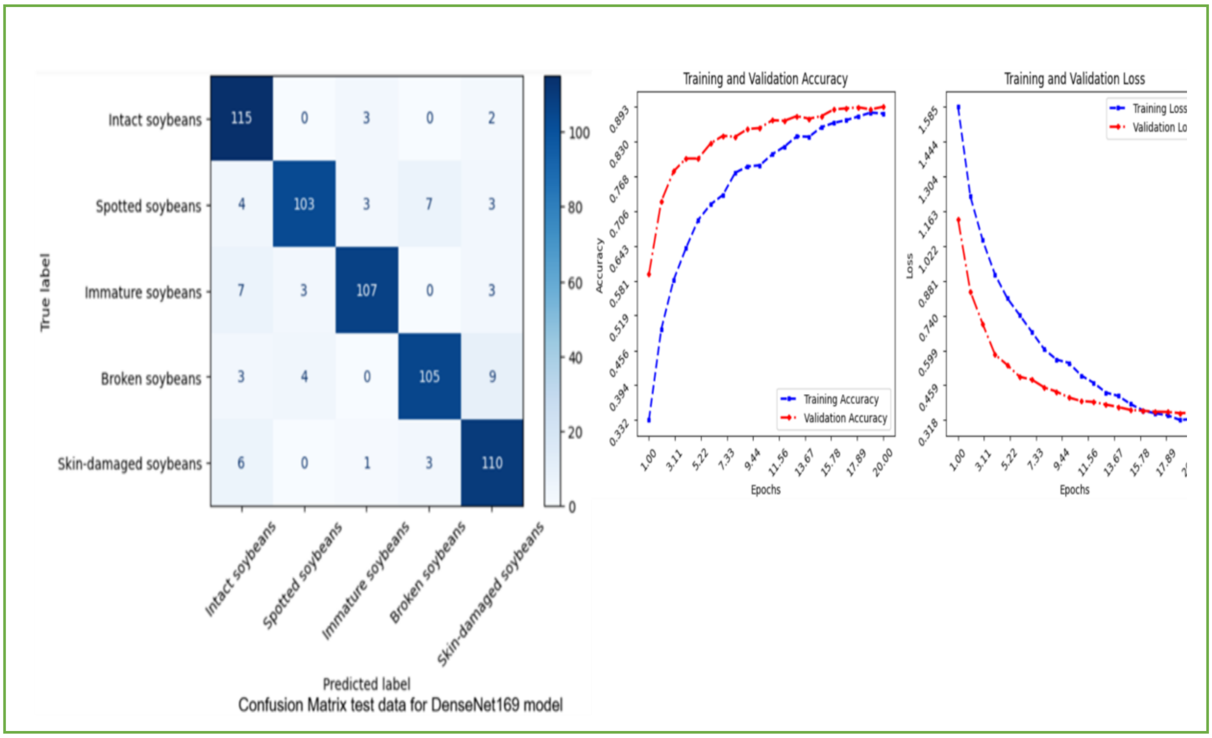


*Figure 6: Confusion matrix and train and validation accuracy and loss plot for DenseNet169 model*

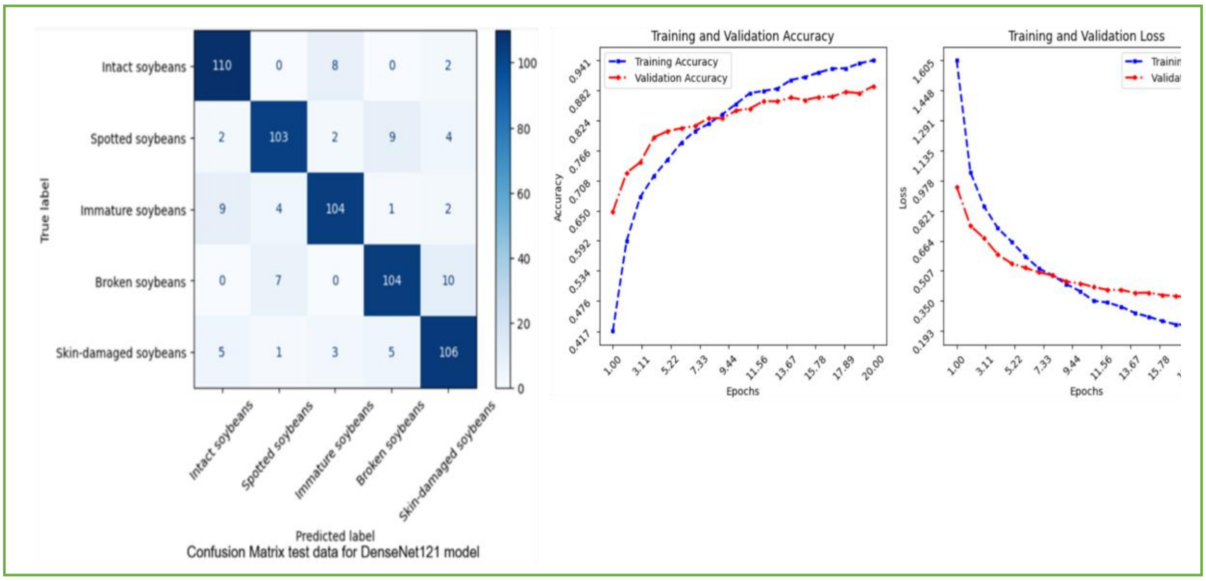


*Figure 7: Confusion matrix, train and validation accuracy, and loss plot for DenseNet121 model*

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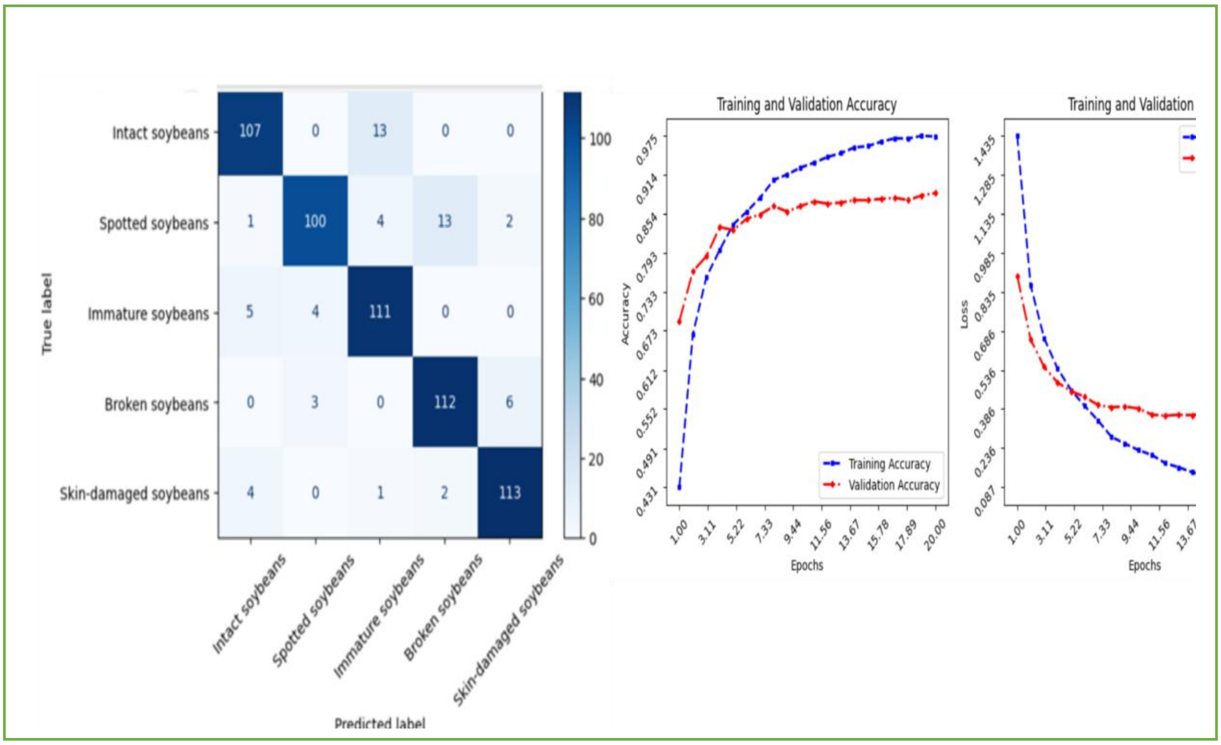


*Figure 8: Confusion matrix and train and validation accuracy and loss plot for DenseNet201 model*

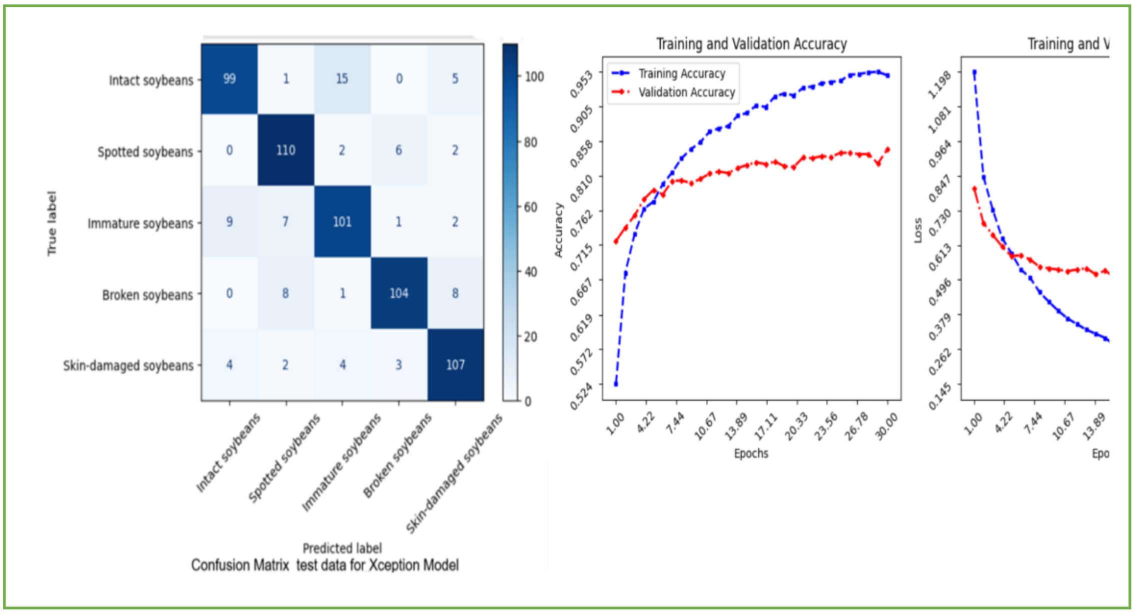


*Figure 9: Confusion matrix and train and validation accuracy and loss plot for Xception model*

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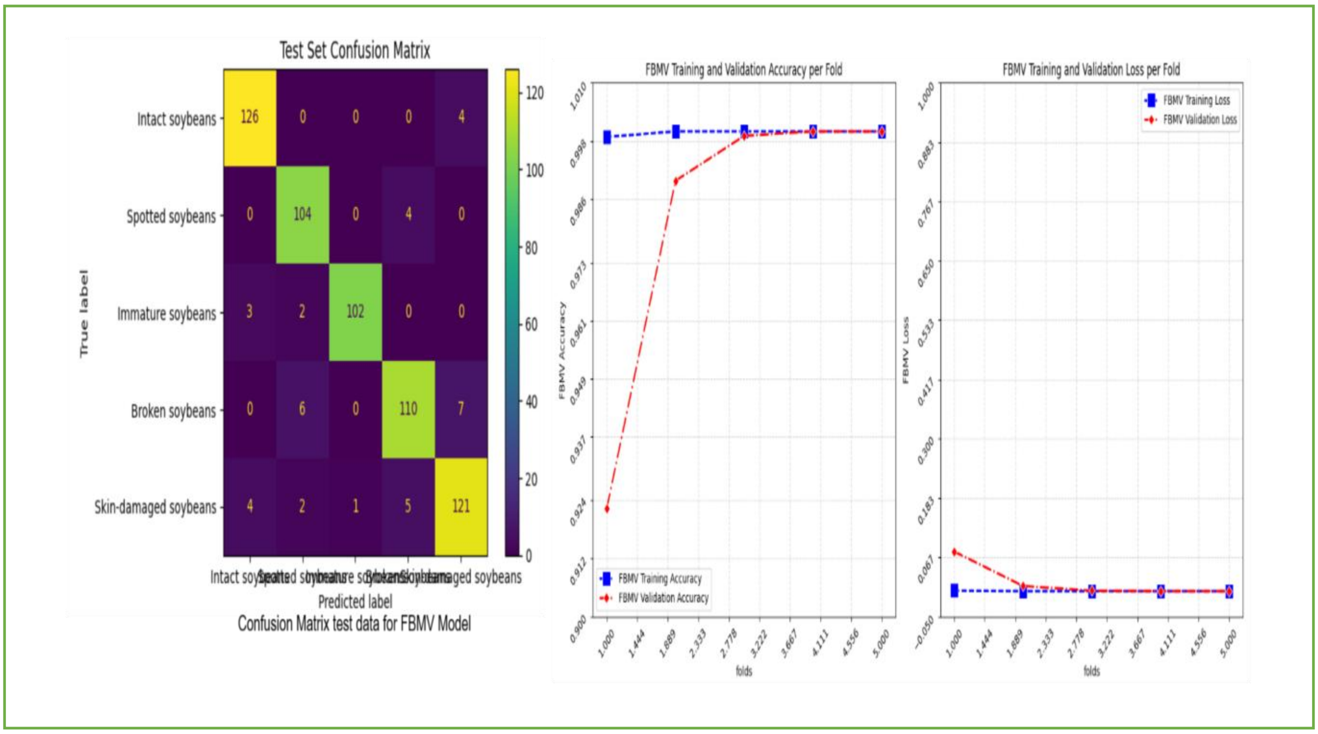


*Figure 10: Confusion matrix, train and validation accuracy, and loss plot for the FBMV model*

## DISCUSSION

While evaluating the effectiveness of convolutional neural network models for classifying soybean seeds, the models achieved strong overall results; our analysis also revealed significant differences. The DenseNet201 and DenseNet169 were the most successful in terms of accuracy, precision, recall, and F1 metrics. These models, which feature a densely interconnected structure, not only facilitate more efficient feature reuse but also help prevent diminishing gradients. As a result, they improve the model's learning speed and stability, which explains its superior performance.

Despite individual machine learning models with decent performances, ensemble learning with majority voting, however, not merely the average but the majority choice of the different models, resulted in a major leap in classification accuracy that exceeded the individual models, with a 98.22% training accuracy and 97.68% test accuracy. Hakim et al. (2025) support the finding, noting that this provides power-up performance through ensemble learning, which is one of the ways it can reduce model variance and thereby increase the model's robustness and generalisation. The exact matching of the accuracy, recall, and F1 scores indicates a well-balanced classification across all classes, a very important factor in the agricultural sector, where incorrectly identifying defective seeds can lead to financial losses or a reduction in crop quality. Kumar et al. (2024) validate the outcomes of ensemble

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learning when applied to deep learning models as a strong approach for soybean seed classification. In addition to improving accuracy and efficacy, it also boosts model longevity and reliability, thereby extending the practical use of a point method for automated quality assessment of agricultural products.

Ghimire et al. (2023) support the finding that deep learning-based models are extremely capable in agricultural image classification, including the analysis and classification of soybean seeds. These deep learning models, especially the DenseNet-based ones, are very good at discovering unique features in datasets because of their dense connectivity, which promotes feature diffusion and improves learning efficiency. Besides, this study achieves superior results with majority voting ensemble learning and outperforms many single-model methods. However, just like other researchers. The model's results depend on the dataset's characteristics. Here, only the controlled imaging setting puts a limit on its generalisation to the outside world. But the presented method is definitely one of the best options for evaluating soybean seed quality.

## CONCLUSION

This paper presents a case study using deep learning (DL) algorithms, particularly convolutional neural networks (CNNs), to automatically segment soybean images into five categories: intact seed spot, immature, broken, and skin-damaged. The experimental results demonstrated that DenseNet201 and DenseNet169 models were more effective than other CNN architectures, such as DenseNet, ResNet, VGG Inception, Xception, and MobileNet, when accuracy, precision, recall, and F1-score were used as metrics. To merge the outcomes of the best models, an ensemble learning strategy based on majority voting was adopted. This not only reinforced but also diversified the model. The ensemble method notably outperformed the classification performance of individual models, achieving a test accuracy of 97.68% and a validation accuracy of 98.22%. These findings indicate that ensemble strategies are an excellent way to overcome the limitations of single models, leading to more precise predictions and more reliable classifications.

Overall, the framework proposed here is a highly precise method that requires less computational time for determining soybean seed quality. Automated agricultural inspection machines can very simply have this method implanted inside. With its implementation, production and seed grading operations will increase in both quantity and quality. Artificial intelligence (AI) tools are highly effective for increasing farm productivity and improving seed sorting and quality evaluation. Researchers should work to make the model more intelligible, and the seed image dataset should be expanded and diversified across backgrounds, angles, and lighting conditions to improve the model's adaptability to real-world production scenarios. Besides, field inspection systems or mobile devices may use real-time versions of lower-complexity networks, such as MobileNetV3 or EfficientNet-Lite.

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