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# Deep Learning Approach for the Morphological Differentiation of Corn Seed Types

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**Abstract**

Corn is one of Indonesia's main food ingredients that contains the second largest source of carbohydrates after rice. Classification of the type and quality of corn seeds is still conducted manually by farmers. This procedure is time-consuming and can result in inaccuracies in sorting. Morphology has important characteristics to determine varieties such as size, color, area and seed shape. Some of these attributes, if measured manually, will take a long time and its complexity requires special expertise. An effective approach for describing these characteristics is using machine learning techniques. The machine learning used is Convolutional Neural Network (CNN). The CNN models used are ResNet50, ResNet101, VGG-19 and MobileNetV2. An analysis of the performance of the model was carried out using a confusion matrix. The results of the CNN model performance parameters for the classification of corn seed varieties with the ResNet50 model showed the best performance with accuracy of accuracy of 92.54%, precision of 90.40%, a recall of 90.84% and an $F_1$-score of 90.26%.

*Key Words*: maize seed, variety classification, machine learning, convolutional neural networks.

## 1 Introduction

Maize is a grain crop from the grass family, originally discovered in the Americas and spread to Asia and Africa by Europeans. Maize was introduced to Asia by the Portuguese in the 16th century. The maize is an annual crop with a life cycle of 80-150 days. A corn kernel consists of three main parts: the pericarp (outer layer), endosperm (food reserve), and embryo (future plant) [?] [?].

Despite its global significance, the increasing number of maize varieties due to selective breeding and regional adaptation presents challenges in accurate variety identification. Traditional classification techniques, which often rely on manual observation of phenotypic traits such as shape, size, and color, are labor-intensive, prone to human error, and lack consistency across evaluators [?]. This may result in misclassification of seed varieties, which directly impacts crop yield, seed purity, and agricultural productivity, particularly in large-scale

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farming and seed certification systems [?] [?] . In addition, phenotypic similarities among different maize varieties further complicate without advanced imaging tools. These challenges highlight the necessity of adopting automated and reliable methods, such as computer vision and deep learning, to support accurate and efficient classification of maize seeds [?].

To address these limitations, recent advancements in computer vision have led to the adoption of deep learning, particularly Convolutional Neural Networks (CNN), as a powerful tool for automating seed classification tasks. CNN-based models can extract hierarchical features from seed images, enabling accurate and consistent classification without relying on subjective visual assessment [?]. It also can be used for seed classification method using SSIDNet achieved accuracy of 98.64%. Among these, lightweight architectures such as MobileNetV2, as well as deeper models like VGG-19 and ResNet, have shown promising results in seed variety classification due to their ability to generalize across complex visual patterns while maintaining high accuracy [?]. For instance, the use of VGG-19 achieved 100% accuracy in classifying corn seed quality, while MobileNetV2 reached an accuracy of 93.33% for Philippine maize variety classification [?]. Several studies have also demonstrated the effectiveness of CNN-based and traditional machine learning models in seed classification. The research in [?] compares six prominent CNN architectures including AlexNet, VGG-16, Xception, GoogLeNet, SqueezeNet, and NasNet-Mobile for weed seed identification, where AlexNet offers strong classification with high efficiency and GoogLeNet achieves the highest accuracy. In a separate study, Rajalakshmi et al. [?] developed RiceSeedNet, a deep neural network that classifies 13 local rice seed varieties with 97% accuracy and further achieves 99% accuracy on eight rice grain varieties, outperforming InceptionResNetV2, InceptionV3, and VGG-16. Moreover, Duc et al. [?] proposed an approach to predict soybean seed weight using morphological features extracted from images, employing machine learning models such as random forest and multiple linear regression, both achieving high prediction accuracy ($R^2 \geq 0.94$). Additionally, Mgomezulu et al. [?] reported that for maize seed classification, K-NN and logistic regression outperformed CNN models due to the low complexity of the data, where CNNs are typically more effective for complex patterns. Implementing CNN-based classification not only reduces human involvement and error but also ensures the scalability of the identification process, making it suitable for deployment in real-time agricultural and seed certification systems [?]. Thus, the development of CNN-based maize seed classification systems becomes essential to support precision agriculture, improve crop management, and ensure genetic purity of cultivated varieties [?].

The structure of this manuscript is organized as follows. Section 1 introduces the background and outlines the challenges in accurately classifying corn seed varieties, emphasizing the limitations of conventional methods. Section 2 elaborates on previous research, particularly those involving imaging techniques and machine learning applications for corn seed classification. Section 3 describes the methodology employed in this study, covering dataset preparation, model selection, and the development process of the classification framework. Section 4 presents the results and provides a comprehensive discussion on the model's performance. Finally, Section 5 concludes the study by summarizing the key findings.

## 2 Previous Works

The internet has evolved into a vital medium for information exchange, which has facilitated the widespread dissemination of electronic journals and scientific literature. In the context of corn seed variety identification, selecting an appropriate model architecture for object classification is crucial. Consequently, a comprehensive literature review has been conducted to examine previous studies employing various machine learning and deep learning approaches for this task. Among these approaches, CNNs have emerged as the most effective method, consistently outperforming traditional algorithms in terms of classification accuracy. The most frequently utilized CNN architectures in recent studies include ResNet, VGG-19, and MobileNetV2.

Numerous studies have validated the superiority of CNNs in corn seed classification tasks. For instance, MobileNetV2 achieved an accuracy of 93.33% in classifying Philippine maize varieties, surpassing conventional machine learning models such as Decision Tree, Naive Bayes, and Linear Discriminant Analysis [?]. Similarly, VGG-19 demonstrated exceptional performance in classifying corn seed quality, attaining an accuracy of 100%, while GoogLeNet and DenseNet201 achieved accuracies of 99.75% and 99.50%, respectively [?]. ResNet-50, also evaluated in the same study, yielded similarly high performance, further reinforcing the effectiveness of residual learning in visual classification tasks. Hybrid models combining CNN and Long Short-Term Memory (LSTM) networks have also been explored. One study employing hyperspectral imaging reported that a CNN-LSTM model achieved an accuracy of 95.26%, outperforming both standalone CNN and LSTM models, which reached 94.74% each [?]. Hamid et al. applied MobileNetV2 using transfer learning and data augmentation, achieving 96.4% accuracy across four corn seed classes [?]. In a related study, Altuntaş et al. utilized VGG-19 for classifying haploid and diploid corn seeds, obtaining an accuracy of 94.22%, a sensitivity of 94.58%, and an *F1*-score of 93.07% [?]. Building upon this, Setiawan et al. applied fine-tuning techniques, achieving an improved accuracy of 96.83% These seeds are photographed and an $F_1$-score of 97.36% [?]. Furthermore, Setiawan and Pramudita employed ResNet50, VGG16, and MobileNet to classify 1,230 haploid and 1,770 diploid maize seeds. Among the models tested, ResNet50 achieved the highest accuracy of 98.16% [?]. Eryigit and Tugrul conducted a comparative analysis of several deep learning architectures for seed classification, highlighting the superior capability of CNN-based models in capturing discriminative visual features [?]. Alkanan and Gulzar proposed an enhanced MobileNetV2-based model incorporating feature augmentation and transfer learning, attaining an accuracy of approximately 96%, with a precision of 0.975 and a recall of 0.963, thereby outperforming other state-of-the-art methods [?]. Suárez et al. investigated the application of few-shot learning in maize seed classification and demonstrated the feasibility of this approach in scenarios with limited training data [?]. Wang et al. introduced a defect detection method combining watershed algorithms with a two-pathway CNN model that leverages both RGB and NIR images. Their approach achieved 95.63% accuracy and outperformed conventional single-path CNN models in identifying defective seeds [?]. Lastly, Isik et al. employed a hybrid architecture consisting of unidirectional and bidirectional LSTM models to forecast maize seed production. Their findings showed improved performance in modeling time-dependent patterns compared to traditional sequential models [?].

# 3 Method

## 3.1 Dataset Preparation

The initial stage of creating a machine learning model to identify corn varieties is to create a dataset related to corn grain varieties. The corn seed sample was obtained from the seed laboratory of Indonesian Ministry of Agricluture in Maros, South Sulawesi. These seeds are photographed to provide the seed images. This image colletion was completed at the Research Center for Data and Information Sciences, Science and Technology Area Samaun Samadikun, National Research and Innovation Agency (BRIN), Bandung, West Java. This dataset has eight class labels where the total images of the dataset have 2701 images. There are eight class labels from the dataset namely B11, CLYN, CY.7, 1026.12; N51; N79; M1214 and MAL03 which represent varieties of corn kernels. Example data for each class can be seen in Figure **??**.

The image data was collected with the equipment shown in Figure **??** The maize seeds were placed at the center point of the photo booth section on a flat surface. A single light source emitted from a white ring LED placed at the top of the corn kernel location was used as the light source. A Canon EOS 70D Digital Single-Lens Reflex (DSLR) camera was used to acquire images of the obtained maize seed samples that had been placed at the center of the photo box. The camera was mounted on a tripod to ensure stability during image capture. The camera used only environmental light from a ring LED lamp placed on top of the photo box [?][?].

## 3.2 Data Preprocessing

The dataset obtained is reprocessed to adapt the images to the system readings, aiming to improve the accuracy of the machine learning results. This process is divided into two stages, namely pre-processing and augmentation. Both stages are done through the online Roboflow platform, which allows direct alteration of the dataset images. In the pre-processing stage, the image dimension is resized from $350 \times 350$ to $640 \times 640$ pixels and also

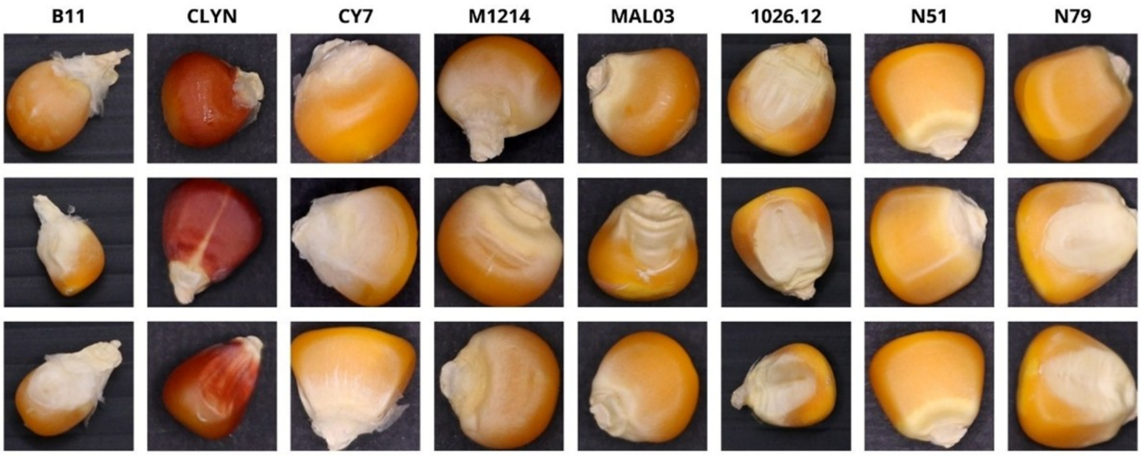



Figure 1: Maize Seed Variety Dataset.

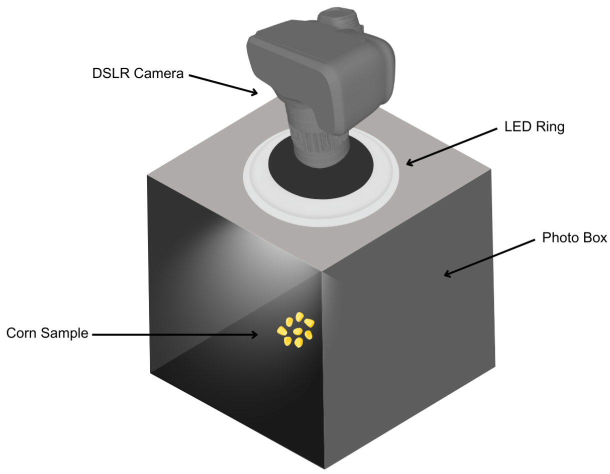



Figure 2: Maize Seed Image Capturing Process.

used fit (reflected edges). Fit (reflected edges) in Roboflow serves to fill empty areas in the image by reflecting the edges of the existing image. This allows images that have empty areas around the edges to be expanded or filled in reflectively, thus ensuring that every object in the image is maintained proportionally and not cut off when processed or analyzed by machine learning models. By using fit (reflected edges), the images can be transformed consistently and ensure that the right information is retained in the data processing process [**?**][**?**]. In addition, auto-orientation is also applied to keep the image pixels unchanging, even when oriented in either landscape or portrait format. The type of pre-processing used can be seen in Figure **??**.

In the corn kernel dataset that has gone through the pre-processing stage, data augmentation techniques such as shear range and zoom range with a value of 20% are used to increase the variety and diversity of the data. By setting the shear range and zoom range to 0.2, the corn kernel images can be distorted or resized up to 20% of their original size. This helps the machine learning model to learn more general patterns and improve its ability to recognize corn kernels in various positions or scales. Shear range and zoom range are applied to create a greater variety of corn kernel images, enriching the training dataset and improving the performance of the object detection model.

Datasets that have gone through pre-processing and augmentation stages will be split into three types of

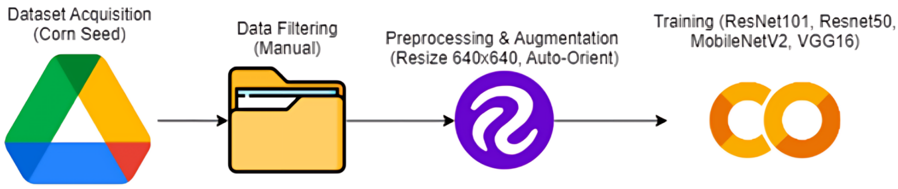



Figure 3: Overview of the Data Preparation and Model Training Pipeline.

data, namely train, validation, and test. Train data is used to train the architecture model that has been designed by performing feature learning, so that the model can learn patterns and remember the correct output results. Validation data is used during the training process to monitor the performance of the model and measure its accuracy in identifying objects. Test data is used to test the accuracy of the final model after going through the training and validation process. The split ratio for these three types of data is 70% for train data, 20% for validation data, and 10% for test data. With this division, the final dataset consists of 1,785 images for train data, 510 images for validation data, and 225 images for test data. By using this proportion, we can ensure that the model is given a large enough dataset to learn well, while also ensuring that we have enough data to evaluate the model's performance well at the final stage. The data sharing ratio can be shown in Figure **??**.

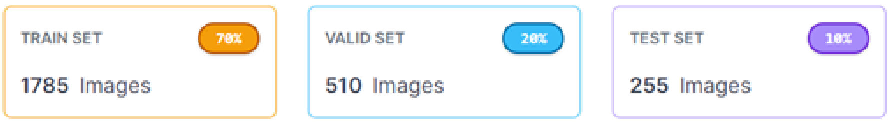


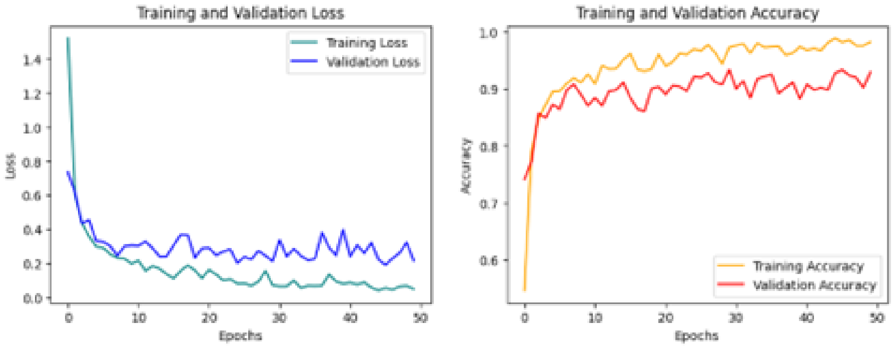

Figure 4: Data Split Process.

### 3.3 Model Development

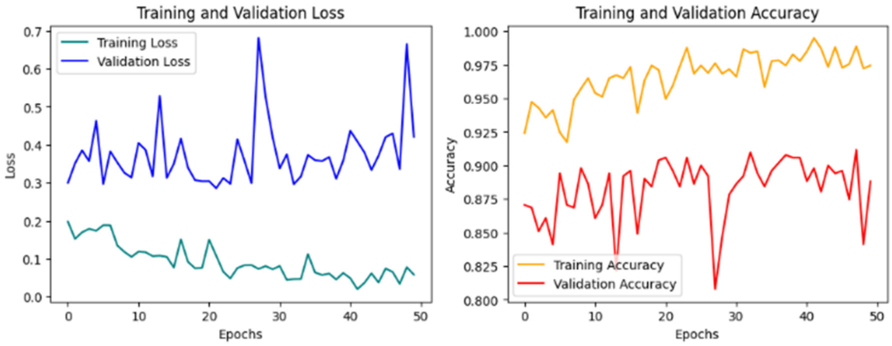
The design of all models was done through the Google Colab platform, which can be accessed online through a web browser. To run each command, the T4 runtime GPU provided by Google Colab is used, but it should be noted that there is a time limit for using the GPU. To optimize model performance while keeping training time manageable, all models were trained using 50 epochs and a batch size of 32. This configuration ensures a balance between sufficient learning iterations and efficient use of computational resources, allowing each model to converge effectively within the constraints of the platform. The accuracy and loss rates at each epoch for different models were analyzed during the training and validation process. For ResNet50, the accuracy during training consistently increased with epochs while the accuracy in validation showed some fluctuation. The highest training accuracy reached 98.88% with an average of 92.9%, while the highest validation accuracy was 93.33% with an average of 90.1%. The loss rate decreased consistently during training and validation with minor variations across the epoch. For ResNet101, the training accuracy fluctuated but tended to rise with epochs, while the validation accuracy increased with epochs. The highest training accuracy was 99.5% with an average of 96.63%, and the highest validation accuracy was 90.7% with an average of 88.2%. The loss rate decreased consistently in training but had some fluctuations in validation. The accuracy and loss rates for VGG-19 and MobileNetV2 showed similar patterns as ResNet101, with fluctuations in training accuracy and consistent decrease in loss rate, while validation accuracy increased with epochs. Accuracy and loss curves for the four models are shown in Figure **??**.

## 4 Result and Discussion

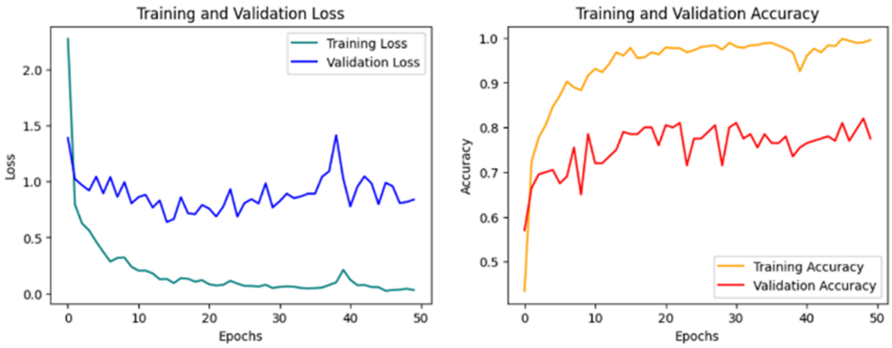
Figure 6 shows the results of confusion matrix analysis for different models (ResNet50, ResNet101, VGG-19, and MobileNetV2) used to read data during testing. In the case of ResNet50, most identifications match



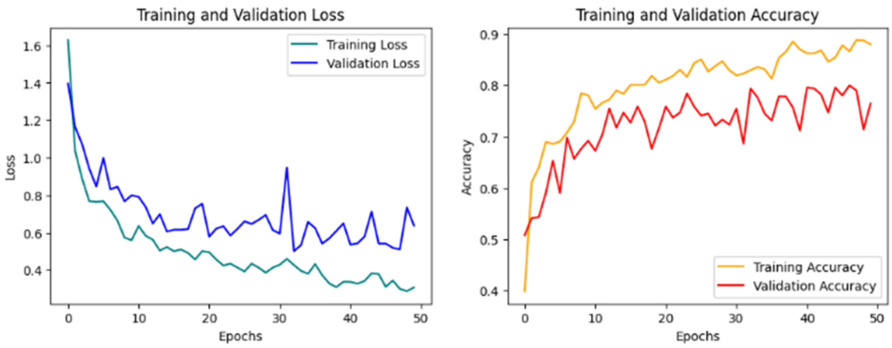

(a) ResNet50




(b) ResNet101




(c) VGG-19




(d) MobileNet2

Figure 5: Training progression based on loss and accuracy values of four different deep learning architectures

the actual and predicted data, with an average error value of 0.0746. However, there is a significant error in identifying the N51 class, often identified as the N79 class, likely due to their similar shapes and colors. The accuracy for ResNet50 is 92.54%. Similar patterns are observed for ResNet101, with an average error value of 0.102% and the highest error in the N51 class, resulting in an accuracy of 89.80%. The VGG-19 model on the other hand, shows many identifications that do not match the actual and predicted data, which may be attributed to overfitting. The accuracy for VGG-19 is 73.34%. Finally, the MobileNetV2 model shows high accuracy for some classes and lower accuracy for others, with an average error value of 0.2353%. The accuracy for MobileNetV2 is 76.47%. Overall, these models demonstrate varying levels of accuracy and error in identifying different classes of data.

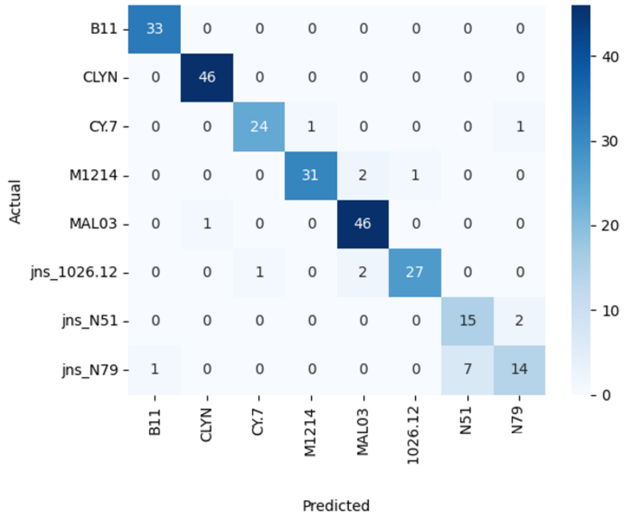
After going through the training and testing stages on each model, the final step is to evaluate the performance and compare them with each other. The evaluation is done by calculating several parameters such as accuracy, recall, precision, and $F_1$ score. These calculations are based on the confusion matrix that has been created for each model. Table 1 displays the accuracy, recall, precision, and $F_1$ score values generated during the testing phase on the ResNet50, ResNet101, MobileNetV2, and VGG-19 models. From Table 1, it can be described that ResNet50 achieved the highest performance, with an accuracy of 92.54%, recall of 90.40%, precision of 90.84%, and $F_1$-score of 90.26%, outperforming ResNet101 despite having fewer parameters and slightly longer training time. This result is consistent with previous findings, which indicate that ResNet50 can often match or exceed the performance of deeper architectures like ResNet101, especially on mid-sized datasets, due to its optimal balance between model depth and generalization [?]. The performance discrepancies among models like MobileNetV2 and VGG-19 can be attributed to differences in model size and the ability to generalize. ResNet models particularly ResNet50 and ResNet101 perform better due to their residual connections, which mitigate the vanishing gradient problem leading to more effective learning and higher accuracy [?][?]. MobileNetV2, while more efficient tends to sacrifice some accuracy for faster processing particularly on smaller datasets [?][?].

Table 1: Performance comparison of different CNN models for maize seed classification.

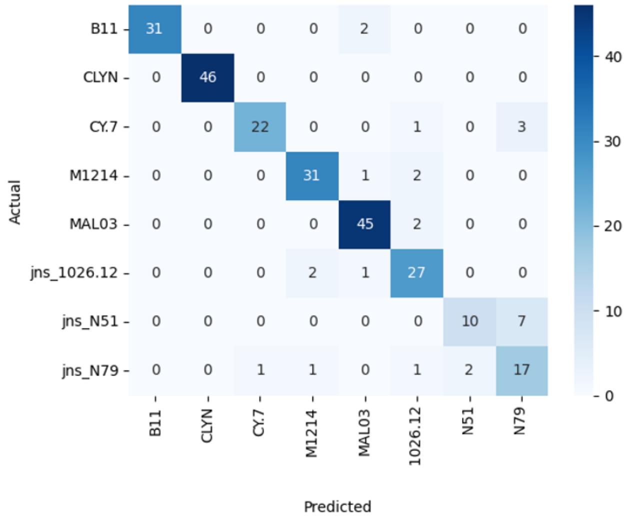
| **Model** | **Size (MB)** | **Training Time** | **Accuracy** | **Recall** | **Precision** | **$F_1$ Score** |
|---|---|---|---|---|---|---|
| ResNet50 | 98.02 | 02:54:05 | 92.54% | 90.40% | 90.84% | 90.26% |
| ResNet101 | 170.76 | 00:56:13 | 89.80% | 88.30% | 86.90% | 86.40% |
| VGG-19 | 78.42 | 01:09:26 | 76.47% | 78.80% | 66.80% | 71.10% |
| MobileNetV2 | 13.65 | 02:22:12 | 73.34% | 69.80% | 69.00% | 69.80% |

Maize seed variety N79 is often misclassified as N51 and 1026.12, which highlights the significant visual similarity in kernel morphology. N79 kernels are characterized by a round, compact structure and prominent yellow-orange pigmentation across their surface. These chromatic and textural features are very similar to N51 kernels, creating classification challenges, especially for lightweight models like MobileNetV2. The limited color contrast of the N79 seed coat further reduces its visual uniqueness, compounding the problem of misidentification.

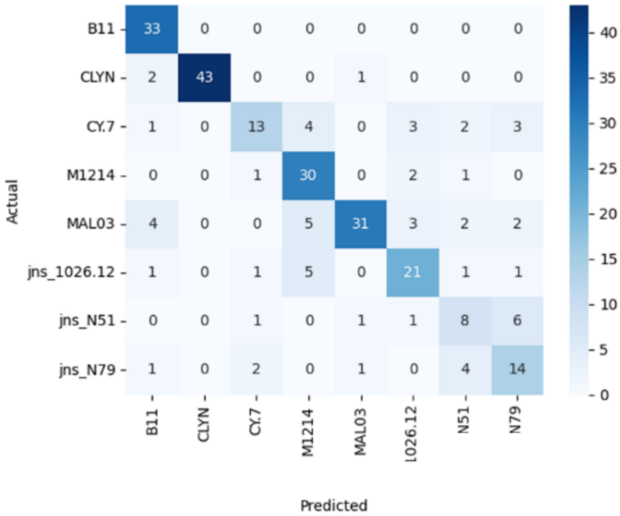
In contrast, N51 seeds show a slightly elongated shape with a uniform golden color. The key point of visual overlap lies in the surface reflection and its symmetrical gloss pattern, which mirrors that of N79. Under consistent lighting, the specular highlights on N51 seeds often resemble N79, both in spatial placement and morphology. Convergence in physical attributes-such as size, surface luster, and pigment distribution-increases classification ambiguity, especially under uniform illumination or homogeneous backgrounds. The comparison of the seed images of the three classes can be seen in Figure 7.



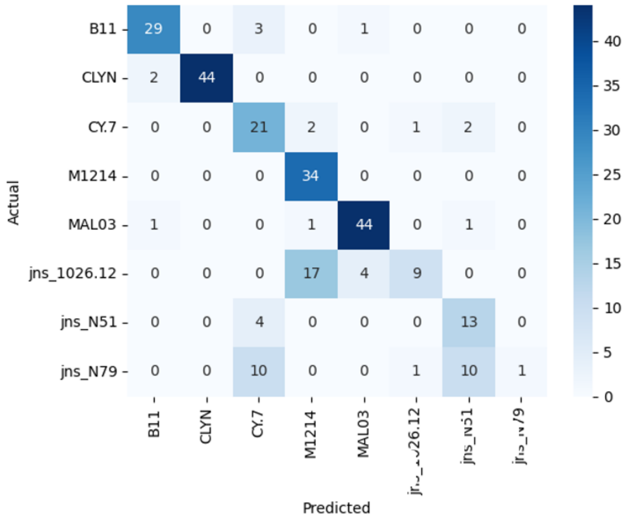

(a) ResNet50




(b) ResNet101




(c) VGG-19




(d) MobileNetV2

Figure 6: Confusion matrix of several deep learning architectures.

(a) 1026.12

(b) N79

(c) N51

Figure 7: Example Types of Classification Errors (a) 1026.12, (b) N79, (c) N51.

# 5 Conclusion

Based on the results of the research and discussion, the classification of corn seed varieties using Convolutional Neural Network (CNN) architecture has proven effective in identifying visual differences between classes. Performance evaluation using four CNN models MobileNetV2, VGG-19, ResNet50, and ResNet101 - showed varying results in terms of accuracy, precision, recall, and $F_1$ score. MobileNetV2 achieved the lowest average performance with 73.34% accuracy and 69.8% $F_1$ score, followed by VGG-19 with 76.47% accuracy and 71.1% $F_1$ score. ResNet50 performed better with 86.27% accuracy and 83.4% $F_1$ score, while ResNet architectures outperformed the others, with ResNet50 achieving the best overall performance with 92.54% accuracy, 90.40% recall, 90.84% precision, and 90.26% $F_1$-score surpassing even ResNet101, which achieved 89.8% accuracy. These results indicate that ResNet50 offers a more optimal trade-off between model depth, learning capacity, and generalization, particularly on medium-scale image classification tasks. The improved performance of ResNet50 is supported by its residual connections, which help preserve feature information and ensure stable gradient flow during training, resulting in faster convergence and higher accuracy. While ResNet101 still demonstrated strong capabilities, its deeper structure did not provide a significant advantage in this case and may have introduced unnecessary complexity or overfitting. Additionally, confusion matrix analysis showed that ResNet50 achieved fewer misclassifications across most corn seed classes, including visually similar classes like N79 and N51, reinforcing its robustness and reliability in practical applications.

Model complexity, dataset size, and network depth also influence architecture selection. MobileNetV2, although efficient and lightweight, sacrifices performance and is more suitable for real-time or embedded applications with limited resources. VGG-19, although deeper than MobileNetV2, tends to be unsuitable for smaller datasets due to the lack of residual connections. Meanwhile, ResNet architectures, especially ResNet50, show the best balance between depth, learning ability, and classification accuracy. Therefore, based on the evaluation results, ResNet50 is considered the most reliable architecture for classifying corn seed varieties using CNN. Despite the relatively higher training time and model size, the accuracy and $F_1$ score achieved make it a suitable choice for use in precision agriculture systems. The model was able to classify each corn variety effectively, and the classification system has the potential to be further improved applying the of attention mechanisms or larger training data sets.

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