 ISSN 2502-3357 (online) | ISSN 2503-0477 (print)

Contents lists available at www.journal.unipdu.ac.id

Register

Journal Page is available to www.journal.unipdu.ac.id/index.php/register

Research article

Comparison of Convolutional Neural Network Methods for the Classification of Maize Plant Diseases

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ARTICLE INFO

Article history:
Received 17 June 2023
Revised 30 January 2024
Accepted 12 March 2024
Available online 31 March 2024

Keywords:
Corn Disease Classification,
Convolutional Neural Network Models,
Image Analysis Algorithms,
Disease Detection Accuracy,
Agricultural Technology Innovation

IEEE style in citing this article:
M. I. Abas, S. Syarif, I. Nurtanio, Z. Tahir "*Comparison of Convolutional Neural Network Methods for the Classification of Maize Plant Diseases*", Register: Jurnal Ilmiah Teknologi Sistem Informasi, vol. 10, no. 1, pp. 46-59, 2024.

ABSTRACT

The focus of this study is the classification of maize images with common rust, gray leaf spot, blight, and healthy diseases. Various models, including ResNet50, ResNet101, Xception, VGG16, and ENet, were tested for this purpose. The dataset used for corn plant diseases is publicly available, and the data were split into separate sets for training, validation, and testing. After processing the data, the following models were identified: the Xception model epoch with an accuracy of 83.74%, the ResNet model with an accuracy of 97.19% at epoch 8/10, the ResNet101 model with an accuracy of 97.55% at epoch 10/10, and the ENet model with an accuracy of 98.69% at epoch 9/1000. ENet exhibited the highest accuracy among the five models at 98.69%. Additionally, ENet achieved an average accuracy of 95.45%, the highest among all tested models, based on the average accuracy in the confusion matrix. This research indicates that ENet performs best at processing data related to maize plant diseases. Consequently, the analysis of maize plant diseases is expected to evolve as a result of this research. Following the implementation of the system's generated model, this research will continue to explore its impact. The intention is to provide a summary of the comparative classification performance of CNN algorithms.

1. Introduction

The area of machine learning that has recently seen widespread use across various industries is deep learning. Various tactics have been devised to cater to diverse learning styles, including unsupervised, semi-supervised, and supervised learning. According to a plethora of experiments, deep learning algorithms outperform standard systems in image processing, computer vision, and pattern recognition [1]. For object detection and categorization, AlexNet, GoogLeNet, and ResNet50 stand out as the most widely used convolutional neural networks (CNNs). Various image datasets are available to assess the effectiveness of different CNN architectures [2]. Transfer learning and deep learning algorithms have been employed for pattern identification and classification tasks in some real-world applications and hierarchical systems. However, real-world machine learning environments frequently contradict this notion, as obtaining training data can be costly or challenging, and creating high-performance systems that can handle input from various sources is a constant requirement. This study aims to analyze the applications of deep learning and transfer learning in various fields, provide a clear explanation of transfer learning, offer up-to-date solutions, and utilize deep learning to identify high-level representational features.

Early detection of plant diseases is essential for effective management and decision-making to protect agricultural productivity and quality. Numerous studies in this field have focused on deep

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learning, particularly deep convolutional neural networks (CNNs), which are powerful tools for image processing [3]. Corn diseases include leaf blight, downy mildew, grasshopper pests, and southern leaf blight [4], [5]. Additionally, several studies on corn kernels have been conducted [6]. In image processing, detecting RGB colors and local features such as scale-invariant feature transform (SIFT), sped-up robust features (SURF), Oriented FAST and rotated BRIEF (ORB), as well as object recognition techniques like the histogram of oriented gradients (HOG), are essential [7].

Characteristically, several diseases of maize include leaf spot disease, leaf blight disease, midrib blight, and symptoms of stem borer attacks. Research on imagery is indeed a common focus for researchers, especially in detecting corn kernel images [8] and corn plant diseases using CNNs [9]. However, diagnosing maize leaf diseases in real field settings presents numerous challenges, including complex background noise, variation and irregularity in lesion regions, and significant intra-class and inter-class variances. Analyzing multiple CNN algorithms has yielded the best results [10].

One of the advantages of CNNs is their ability to automatically extract features [11], [12] and even recognize nine different types of diseases and pests [13]. The effectiveness of the CNN algorithm has been proven in various fields beyond corn disease [14]. However, selecting the best architecture and set of hyperparameters from the possible combinations can be a significant challenge. Previous research has focused on hyperparameter tuning for CNNs [15], [16], [17], particularly in medical image processing. CNN hyperparameter optimization has also been applied to automatically classify mosquito morphology, achieving an accuracy of 97.3% [18].

Due to its high accuracy, previous researchers have utilized the ECNN in conjunction with the CNN algorithm [19]. Research opportunities abound for diagnosing corn diseases, particularly in the utilization of the CNN algorithm [20]. Previous studies suggest further enhancement and combination of neural network classifications with Deep Learning, as well as exploring various combinations such as class, dataset size, and learning speed [21]. In the past, convolutional neural networks (CNNs) have been employed for identifying plant diseases, such as in a leaf identification system. This system can distinguish five varieties of native Malaysian leaves—acacia, papaya, cherry, mango, and rambutan—by analyzing leaf photos taken with a cell phone. The network is trained using CNN from deep learning for image classification. An architecture called ResNet-50 has been utilized to train artificial neural networks for leaf recognition and image classification [22].

Previous studies have shown several advantages in terms of algorithms, datasets, and their utilization. For instance, a study by [23] employed the Enhanced Convolutional Neural Network (ECNN) algorithm for identifying maize plant diseases. The four aspects used in the implementation of ECNN are the ECNN framework, fused dilated convolutional layer, one-dimensional convolutional layer, and ECNN motivation. The dataset comprised 500 images classified into 9 classes. The parameters analyzed include f-measure, accuracy, recall, and precision.

Another advantage of the research [24] is the use of a new generation algorithm from CNN, namely CNNs, which enables the developed model to recognize 13 types of corn plant diseases from healthy leaves [25]. This model also demonstrates the ability to distinguish plant leaves from surrounding objects. Additionally, the algorithm's steps have been validated by agricultural experts. The experimental results indicate a precision range between 91% and 98%, with an average precision of 96.3%. In other studies [26], [27], data preprocessing begins with resizing the image to 256x256 pixels for shallow networks, 224x224 for VGG16, VGG19, and ResNet50 and 299x299 for Inception-V3. The study focuses on optimization and prediction models based on the image data. Sample-wise normalization was performed, significantly enhancing the efficiency of end-to-end training. The experiments were conducted on a workstation running Ubuntu, equipped with an Intel Core i5 6500 CPU, 16 GB of RAM, and a GeForce GTX Titan X GPU with 12 GB of RAM. The implementation of the model is supported by the Keras deep learning framework and the Theano backend. Notably, the improved VGG16 model yielded the best results, achieving an accuracy of 90.4%.

This study focuses on comparing multiple CNN algorithms to gain insight into their performance. While previous research has extensively examined the performance of individual algorithms, it has not specifically addressed the comparison of testing methodologies. In this study, we compare CNN approaches such as ResNet50, ResNet101, Xception, VGG16, and ENet. These five algorithms were selected for their strong categorization abilities, allowing for a comprehensive comparison of their performance.

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2. Materials and methods

2.1. State of the Art

A group of researchers trained deep tissue convolution nerves to recognize 26 diseases and 14 plant species. The trained model achieved an accuracy of 99.35% on the hold test set, demonstrating the feasibility of this approach. This method shows a clear path to smartphone-assisted plant disease diagnosis on a global scale by training deep learning training models on expanding, accessible image datasets. To address the issue of over-fitting, we experimented with different ratios of the test set to the training set. We found that the *GoogLeNet case::TransferLearning::Color::20-80* was at a ratio of 20% training set to 80% test set, and the model achieved an overall accuracy of 98.21% (mean F1 score of 0.9820). This high accuracy was achieved despite training the model on only 20% of the data and testing it on the remaining 80%. However, we observed that as we increased the test set to training set ratio, the overall performance of AlexNet and GoogLeNet declined [28].

Based on the experimental findings, the RVM model demonstrates an average recognition rate and prediction speed that are 5.56% and 7.41 times greater, respectively, than those of the Support Vector Machine (SVM). The application takes approximately 1 minute to provide identification results. Therefore, it can be concluded that the system is capable of recognizing wheat diseases and investigating them in real-time in the field [29].

One of CNN's greatest advantages is its ability to automatically extract features by directly processing raw images. The results obtained were very encouraging, achieving an accuracy of 99.18% in the shallow model, which can be used as a practical tool for farmers to protect tomatoes from disease [30].

According to the experimental findings, the proposed convolutional neural network disease identification method achieves an overall accuracy of 97.62%. The model parameters are reduced by 51,206,928 compared to those in the traditional AlexNet model, and the accuracy of the proposed model with the resulting pathological images is increased by 10.83%. This study shows that the proposed deep learning model offers a more effective disease control solution for apple leaf disease with high accuracy and a faster convergence rate. Additionally, the image generation technique proposed in this paper can improve the robustness of the convolutional neural network model [31].

The images within the zero-level set are retained while those outside are set to black as the RPN algorithm's output is fed into the Chan-Vese algorithm for picture segmentation. For the leaf-picking parameter settings, ResNet-101 was chosen as the pretraining model, and the network was trained using a simple background disease leaf dataset in this paper.

The classification number was adjusted from 1000 to 4 to align with the identification of four categories of leaf diseases in this research. All parameters were modified and initialized at the last output layer of ResNet-101. During testing, the image was inputted into the VGG-16 model and the RPN algorithm, where the latter frames the main blade structure, demonstrating superior performance compared to the original model.

The findings indicate that the Chan-Vese algorithm achieves more accurate leaf segmentation after 500 iterations. While the Chan-Vese method may not excel at extracting blade edge contours compared to the DAS algorithm, it effectively preserves the entire structure of the central bar, including leaf veins, color spots, and point shapes. This technique can be valuable for acquiring the complete central structure of the blades, which is essential for disease identification in the subsequent phase [32].

For model training, an open-source database containing nearly 4000 photographs from four distinct classes, including images of healthy plants, was utilized. The VGG19 CNN architecture with transfer learning outperforms the other models by obtaining an overall accuracy of 95%, satisfying the need to create a reliable and efficient classification model. Furthermore, increasing the volume of training data was found to improve the performance of the generated model. The results of applying transfer learning to the CNN architecture are promising and could be further refined to create a comprehensive system for identifying plant diseases that can operate effectively in real-world settings. This system can enable rural areas to diagnose illnesses and initiate timely treatment without relying solely on experienced experts [33].

The accuracy of the DenseNet121 test set is 95.98%, which is higher than that of the other four CNN models. In comparison, InceptionV3, ResNet50, AlexNet, and VGG16 achieved accuracies of 95.07%,

https://doi.org/10.26594/register.v10i1.3656

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95.25%, 91.79%, and 93.35%, respectively. The conventional machine learning approach using SVM achieved an accuracy of 73.20%, which is 11.77% higher than the lowest LR accuracy of 61.43%. This highlights the superior performance of convolutional neural networks over traditional machine learning techniques in image identification. The convolutional layers in convolutional neural networks may automatically extract valuable picture information, and fully linked final layers can summarize and correctly classify these features [34].

Simulations were conducted using the CNN architecture with the LeNet-5 and MNIST datasets, as well as with the CifarNet and Cifar-10 datasets. These simulations demonstrate the potential for performance improvement by tuning the hyperparameters of the CNN architecture proposed in previous studies.

To minimize the number of weights and biases that the CNN built from the resulting harmony vectors needed to train, the research was done by updating the HM. The termination criteria were specified to merge the harmony vectors of HM into a single harmony vector. Simulation results show that HM converges towards a single harmony vector [35].

This research focuses on improving the accuracy of the CNN model by optimizing the selection of CNN architectural parameters, specifically the optimization method and loss function. Seven gradient descent-based optimizers—Stochastic Gradient Descent (SGD), Adaptive Gradient (Adagrad), Adaptive Delta (Adadelta), Root Mean Square Propagation (RMSProp), Adaptive Momentum (Adam), Adaptive Max Pooling (Adamax), and Nesterov's Adaptive Momentum (Nadam)—are compared. According to the testing findings, Adam is the most effective optimizer to improve LeNet's ability to handle relationships between the pigment content of digital images. However, when resources for experimentation are limited, using Adadelta and Adamax is a wise choice to minimize risk [36].

Using a dataset comprising 1,187 photos of various insects and 7,561 images of target mosquitoes, a CNN was trained to automatically classify mosquitoes based on their morphology. Various neural networks, such as Xception and DenseNet, were employed to create automatic categorization models based on these photos. To select hyperparameter settings and enhance model accuracy, a structured optimization procedure utilizing random search and grid search was created.

During the testing phase, the optimized model achieved a balanced accuracy (BA) of 93.5% in classifying target mosquitoes and other insects, and a BA of 97.3% in distinguishing Aedes genus mosquitoes from Culex mosquitoes. The results provide basic information for performing automatic morphological classification of mosquito species [37].

2.2. Methods

Image processing is a technique used to modify or process 2-dimensional images. One definition of image processing is "all operations to correct, analyze, or change an image" [38]. The methods used in this research are the VGG16, ResNet50, ResNet101, Xception, and ENet models. A convolutional layer with a modest convolutional filter specification (33) is used in the CNN model VGG16. More convolutional layers can be added to the neural network to increase its depth depending on the convolutional filter's size.ResNet50.

ResNet-50 is a ResNet variation containing 50 layers. Unlike ResNet-40, which skips 2 layers and connects only once, ResNet-50 passes through 3 levels and includes a 1x1 convolution layer. The number of weights updated during the data training process is referred to as the learning rate. A convolutional neural network with 101 layers in depth is called ResNet-101. It is possible to load convolutional neural networks that have already been trained with over a million images from the ImageNet database. The trained network can identify 1,000 distinct object categories from pictures, including pencils, keyboards, mice, and other animals. The network has been investigated for a range of images, providing feature-rich representations. The input size of the network is 224 by 224 pixels [39].

Xception is a convolutional neural network with a depth of 71 layers. The comparative analysis method used in this study demonstrates that the Xception method outperforms current approaches. Based on experimental results, the suggested method is meant to help radiologists diagnose different lung ailments more accurately [40]. ENet is a semantic segmentation architecture that utilizes a compact encoder-decoder architecture. Some design options include using the SegNet approach to downsampling store the index of the selected element in the maximal merge layer and then using it to

https://doi.org/10.26594/register.v10i1.3656

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generate an infrequently upsampled map in the decoder [41]. The research phase begins with collecting public data online to identify types of corn plant diseases. The dataset being sought is a public dataset that has been validated by the dataset provider. Collecting data on corn plant disease is very important to obtain a large amount of image data, which will be directly trained and analyzed using the CNN algorithm. This process is to determine the accuracy of CNN. The dataset is taken from the Corn or Maize Leaf Disease Dataset. The corn disease dataset consists of Commont Rust (1306 images), Gray Leaf Spot (574 images), Blight (1146 images), and Healthy (1162 images) (Fig. 1).

https://www.kaggle.com/datasets/smaranjitghose/corn-or-maize-leaf-disease-dataset

(a) (b)

(c) (d)

Fig. 1. Sample of the dataset: (a) Common Rust (b) Gray Leaf Spot (c) Blight (d) Healthy

While CNN and MLP both function similarly, CNN represents each neuron in two dimensions, unlike MLP's single dimension [42]. The CNN architecture includes more layers compared to a neural network. The convolutional network can be seen in Figure 2 below.

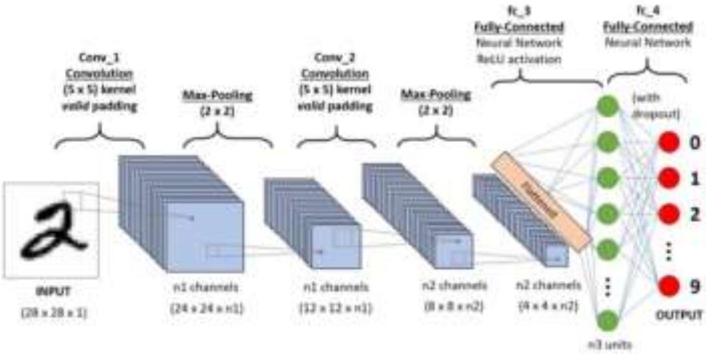

Fig. 2 CNN Architecture [43]

The CNN algorithm is a deep learning system that distinguishes one item from another by taking input photos and applying weighting and biasing to different characteristics or objects in the image. CNN requires much less preprocessing than other classification techniques [44]. CNN is a popular neural network model inspired by the visual perception principles of biological systems. Its history began in the mid-90s and quickly advanced in the late 1900s. A study titled "LeNet-5: A Multi-Layer Artificial Neural Network for Handwritten Number Classification" was published in 1990 by a group of authors. It can identify patterns in images even at low pixel counts with minimal to no preprocessing [45]. Among several CNN models, including ResNet, LeNet, and others, ENet demonstrates superior performance and the fastest training time [46].

https://doi.org/10.26594/register.v10i1.3656

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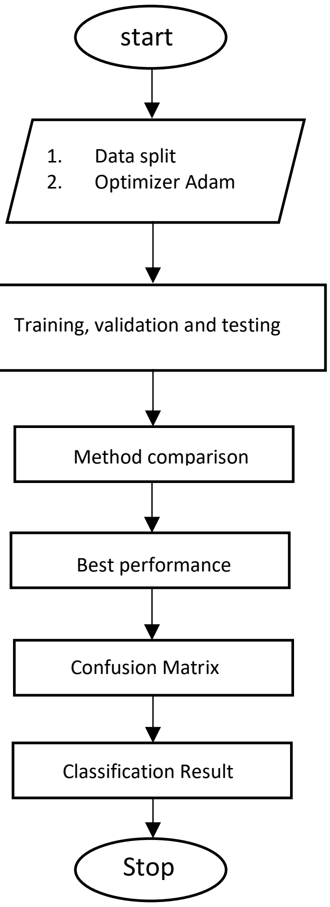

Fig. 3. Research stages

This research consists of the following six steps, as shown in Fig. 3: optimization and data separation for the corn leaf disease dataset, performance evaluation to assess the success of testing, validation, and training, comparison of five strategies to identify the most effective one, obtaining acceptable accuracy values through multiple tests, evaluation of performance using the confusion matrix, and class group classification for maize plant diseases.

3. Results and Discussion

This section details the research concept and implementation for five algorithms: VGG16, ResNet50, ResNet101, Xception, and Enet, with the tested parameters consisting of epoch, accuracy, val_loss, and val_accuracy. The results of the analysis show that the ENet model outperforms the other four models, achieving a high accuracy of 98.69%. Our study compares different approaches for each experiment in terms of epochs. Compared to the other four CNN algorithms, the findings suggest that ENet performs best at epoch 9, with an accuracy value of 98.69% and val_accuracy of 95.45%. This result demonstrates ENet's strong performance in classification. Further study can focus on the implementation stage and beyond for more thorough hyperparameter tuning through the testing of numerous other parameters and optimization techniques.

The best model is constructed from VGG16 by incorporating Flattens, adding Dense 256 with ReLu activation, implementing Dropouts, and integrating Dense 4 with softmax activation, as seen in Fig. 4 and Fig. 5.

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 ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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Model: "sequential"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14714688
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 256)	6422784
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 4)	1028

Total params: 21,138,500
Trainable params: 21,138,500
Non-trainable params: 0

Fig 4. VGG16 models

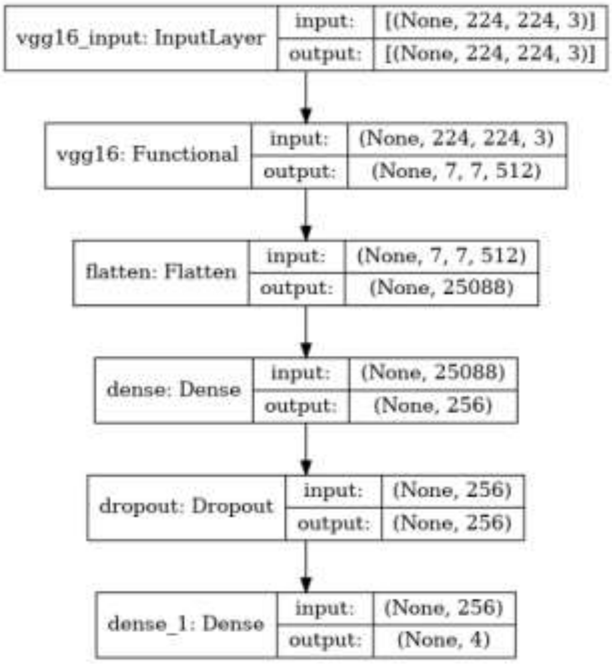

Fig 5. Plot model VGG16

 https://doi.org/10.26594/register.v10i1.3656

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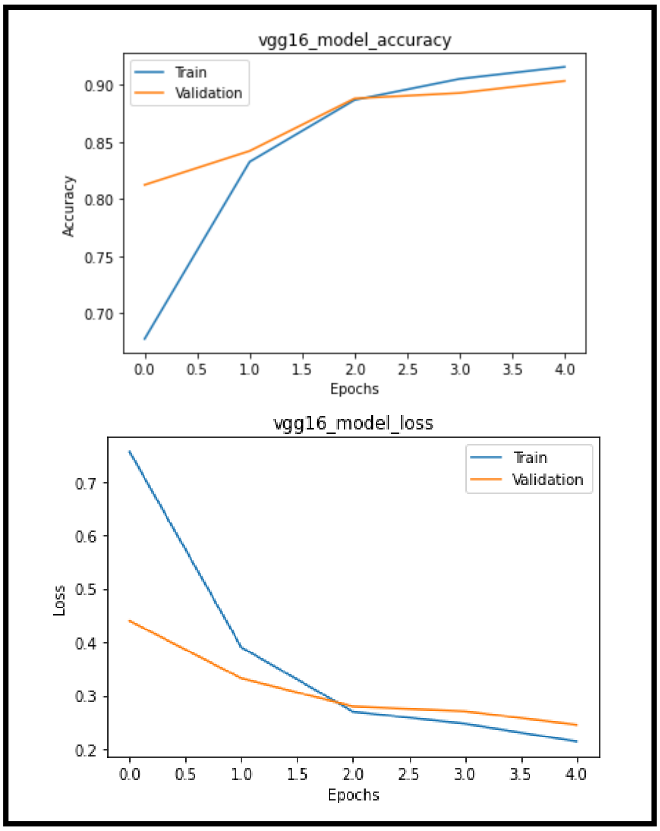

Fig 6. Accuracy and loss graph for VGG16 model

Fig. 6 illustrates that the difference in the graph model between accuracy and loss is not significantly different for both training and validation. This shows that VGG16 also achieves good accuracy in the classification of corn plant diseases, which is the focus of this research.

Table 1. ResNet50 Models

Epoch	Accuracy	Val_loss	Val_accuracy
1	0.8553	0.3130	0.9176
2	0.9051	0.2068	0.9379
3	0.9263	0.2051	0.9331
4	0.9406	0.2067	0.9415
5	0.9505	0.2341	0.9295
6	0.9552	0.2829	0.9379
7	0.9642	0.2500	0.9271
8	0.9636	0.1903	0.9498
9	0.9714	0.2473	0.9427
10	0.9719	0.2612	0.9427

Table 1 displays the ResNet50 model's accuracy, val_loss, and val_accuracy parameters from epochs 1 through 10. Epoch 10 shows the best values for these parameters, indicating optimal training results. To ensure accurate comparison across all experiments, the training procedure for each algorithm considered follows the same setup.

 https://doi.org/10.26594/register.v10i1.3656

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Table 2. ResNet101 Models

Epoch	Accuracy	Val_loss	Val_accuracy
1	0.8651	0.3960	0.8877
2	0.9042	0.2051	0.9116
3	0.9242	0.2208	0.9283
4	0.9394	0.2293	0.9319
5	0.9526	0.2177	0.9379
6	0.9615	0.2074	0.9355
7	0.9657	0.1942	0.9403
8	0.9678	0.1951	0.9379
9	0.9743	0.2198	0.9474
10	0.9755	0.2408	0.9367

Table 2 demonstrates that the ResNet101 model achieves the best value at epoch 10 for the parameters accuracy, val_loss, and val_accuracy from epoch 1 to 10. We conducted identical tests for each method under comparison, and it is possible that extending the experimentation period to higher epochs could improve or decrease performance.

Table 3. Xception models

Epoch	Accuracy	Val_loss	Val_accuracy
1	0.7123	0.6172	0.7587
2	0.7759	0.5384	0.7849
3	0.7929	0.5616	0.7754
4	0.8024	0.5367	0.7778
5	0.8075	0.5446	0.7658
6	0.8251	0.4719	0.8065
7	0.8201	0.4752	0.8100
8	0.8323	0.4844	0.8136
9	0.8374	0.4646	0.8100
10	0.8362	0.4504	0.8399

Table 3 displays the Xception model's values for the parameters accuracy, val_loss, and val_accuracy from epoch 1 to 10. The model achieves its best value in epoch 9 for accuracy, as shown in the table. In the study, the Xception model performs poorly compared to other algorithms. This could be influenced by both the dataset and different experimental settings. While other studies show good performance, our study's model performs the worst in classifying corn plant diseases.

Table 4. The Accuracy Results

Architecture	Epochs	Mean Accuracy	Mean Loss
ResNet50	10	94.19%	17.73%
ResNet101	10	94.32%	16.61%
Xception	10	80.56%	50.84%

Table 4 presents the accuracy results of three algorithms: ResNet50, ResNet101, and Xception. The ResNet101 architecture achieves scattered accuracy values of 94.32% with a mean loss of 16.61%.

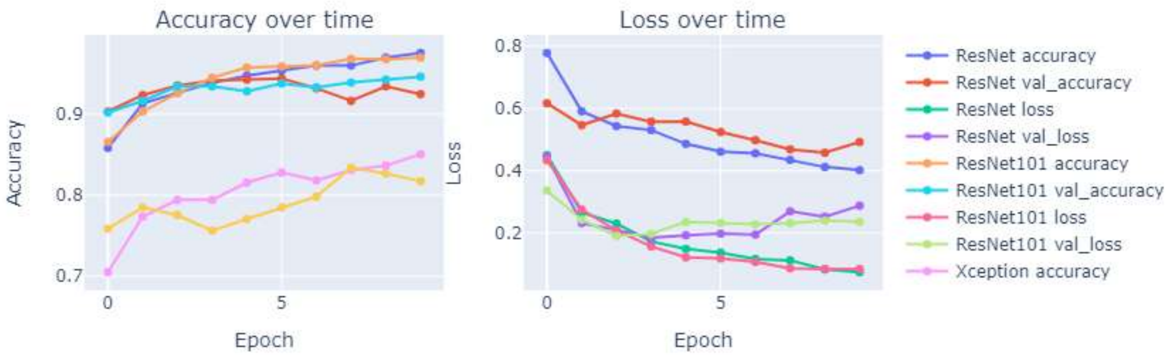

Fig. 7. Comparison of the ResNet50, ResNet101 and Xception models

Fig. 7 shows the plots for each model produced, including ResNet50, ResNet101, and Xception. These three algorithms utilize hyperparameter tuning with GlobalAveragePooling2D, Dense512, ReLU activation, Dropout (0.5), and RMSProp optimizer. The Fig. illustrates that ResNet50 and ResNet101

https://doi.org/10.26594/register.v10i1.3656

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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have similar accuracy and loss values in each experiment. However, ResNet101 achieves a better value than the other two algorithms. Presently, ResNet's performance in our investigation is sufficient for categorization. Better outcomes for the ENet algorithm may arise from future experiments. This comparison of our research allows for further evaluation for the same classification.

Table 5. ENet Model

Epoch	Accuracy	Val_loss	Val_accuracy
1/1000	0.8284	0.5839	0.7751
2/1000	0.9287	0.3176	0.8983
3/1000	0.9446	0.2355	0.9115
4/1000	0.9574	0.1600	0.9498
5/1000	0.9693	0.1376	0.9533
6/1000	0.9773	0.1321	0.9533
7/1000	0.9813	0.1261	0.9557
8/1000	0.9861	0.1279	0.9569
9/1000	0.9869	0.1257	0.9545

Table 5 shows the Enet model's value for the parameters accuracy, val_loss, and also val_accuracy from epoch 1-9/1000. The model achieves its best value at epoch 9/1000. Considering epoch 2, ENet has performed well, showing a consistent increase in accuracy. Conducting experiments over multiple epochs is necessary to obtain more comprehensive experimental data and achieve the accuracy mentioned in the training execution of each epoch. Ongoing experimentation can undoubtedly lead to greater performance gains.

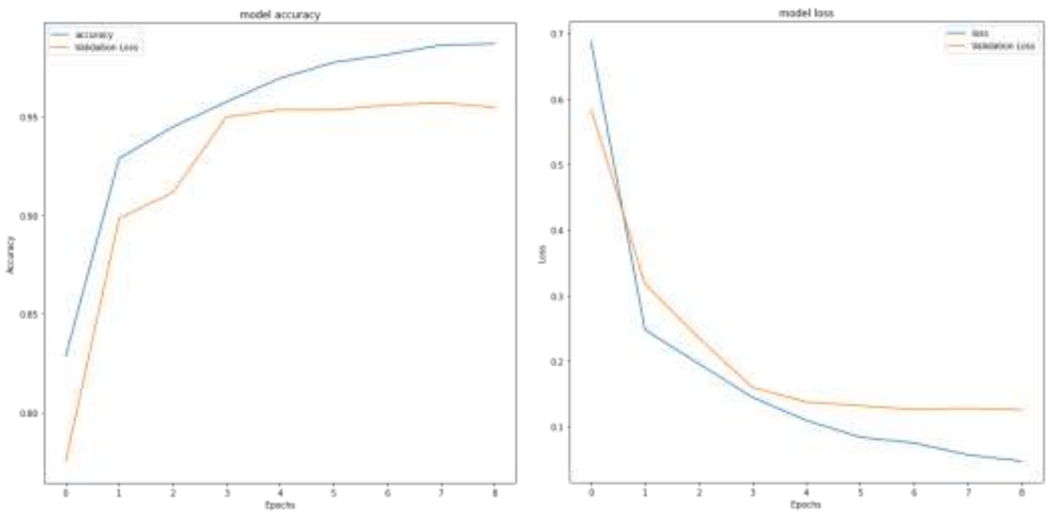

Fig 8. Accuracy and loss graph for ENet model

Fig. 8 shows that the ENet algorithm has the best accuracy and loss model, as indicated by the difference in the graph model between accuracy and loss. Considering that ENet outperforms the other algorithms, researchers recommend conducting extensive experiments on the ENet method and implementing the model. When evaluating an algorithm's performance in an experiment, one might refer to the graph showing the accuracy and loss model. This research has offered a thorough description of employing several algorithms for the same dataset, even though we focus on ENet and have not included any optimization techniques to the experimental process.

From the confusion matrix in Fig. 9, it is evident that the results are quite good, with an average accuracy of 95.45%. This can be used to detect diseases as early as possible. The result of hyperparameter tuning shows that ENet has the highest accuracy among ResNet, Xception, and VGG16. This research enabled us to compare and provide new insights related to the classification comparison of five CNN algorithms. Some limitations of our research include the use of several optimization algorithms, epoch experiments, more algorithm trials, and a more thorough understanding of experiments. Future research should focus on in-depth training using multiple learning rate trials, optimization, and implementation in intelligent applications. This is necessary as the direct application of our experiments in the field is what makes them beneficial to farmers.

https://doi.org/10.26594/register.v10i1.3656

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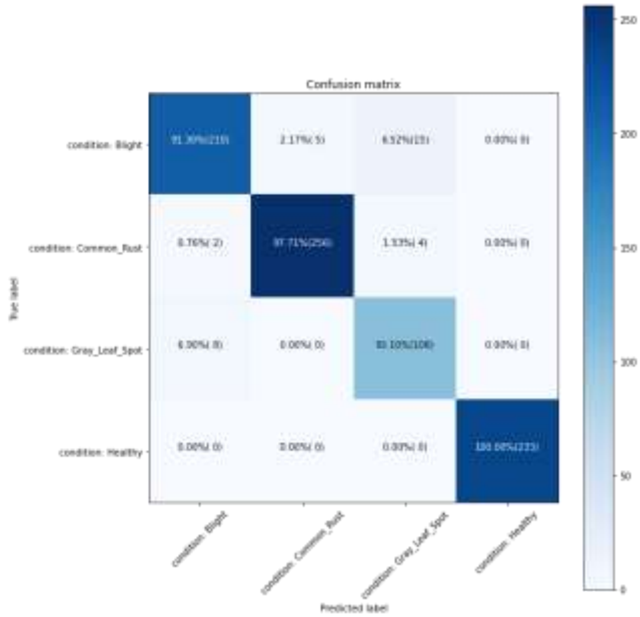

Fig 9. Confusion matrix

4. Conclusions

The modeling findings from ResNet50, ResNet101, VGG16, and ENet suggest that the ENet model achieves a high accuracy value of 98.69% up to epoch 9. This indicates that ENet can effectively classify the dataset related to maize plant diseases, which is the focus of this study. Future research can implement the results of the analysis of the best CNN model found in research on corn plant diseases. Validating the dataset in the field is also crucial for the improvement of this research in the future. ENet performs well because some network layers have been optimized to increase algorithmic efficiency relative to other algorithms in terms of training time, execution speed, and memory utilization. Since we are only comparing five methods in CNN, there is still much to be explored in our research. Future researchers should conduct a more thorough investigation, utilizing ENet to test alternative algorithms that exhibit the highest level of performance according to the results of the literature review. Further research is needed to determine the average accuracy in a confusion matrix. Additionally, to assess the effectiveness of the algorithm employed in the process of real-time maize plant disease detection, a system installation step is also required.

Author Contributions

M. I. Abas: Conceptialization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, and writing – review & editing. S. Syarif: Conceptialization, formal analysis, investigation, methodology, supervision, validation, visualization, writing – original draft, and writing – review & editing. I. Nurtanio: Conceptialization, formal analysis, investigation, methodology, supervision, validation, visualization, writing – original draft, and writing – review & editing. Z. Tahir: Conceptialization, formal analysis, investigation, methodology, supervision, validation, visualization, writing – original draft, and writing – review & editing.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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