JIKO (Jurnal Informatika dan Komputter) Accredited KEMENDIKBUD RISTEK, No.105/E/KPT/2022
Vol. 7, No. 1, April 2024, pp. 36-42 p-ISSN: 2614-8897
DOI: 10.33387/jiko.v7i1.7809 e-ISSN: 2656-1948

IMAGE CLASSIFICATION OF VINE LEAF DISEASES USING COMPLEX-VALUED NEURAL NETWORK

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(Received: 05 April 2024, Revised: 17 April 2024, Accepted: 22 April 2024)

Abstract

Leaf diseases are a severe challenge in the agricultural industry that affects the quality and yield of crops, especially grapes. Early detection and control of disease on grape leaves is an essential aspect of vineyard management. Although traditional detection methods have been used, advances in image processing and deep learning technology offer the potential for more accurate and efficient automation. Artificial Intelligence (AI) and especially machine learning techniques, such as Complex-Valued Neural Network (CVNN), offer a promising approach in this context. This research explores using Complex-Valued Neural Network (CVNN) in image classification of grape leaf diseases. CVNN, with its advantages in handling complex image data, shows potential to improve the accuracy and effectiveness of grape leaf disease detection. The image data was 100 images divided into four classes, Black Rot, ESCA, Leaf Blight, and Healthy, which were collected to train the model. Through experiments, CVNN using the RMSprop optimizer with 100 epochs shows the best performance, achieving the highest accuracy on training at 100 percent accuracy, validation at 89 percent accuracy, and test with 97 percent accuracy with minimal loss. This research highlights the critical role of optimizer selection and training duration in improving model performance.

Keywords: Image Classification, Leaf Disease, Vine, Image Processing, CVNN

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1. INTRODUCTION

Vineyard management plays an important role in ensuring the quality and yield of grapes, which is vital to the agricultural economy [1]. Central to effective vineyard management is the timely detection and control of diseases affecting grape leaves. These diseases can have a significant impact on plant health and productivity. Traditional disease detection methods often rely on visual inspection by experienced agronomists, making them time-consuming and prone to human error [2]. However, recent advances in image processing and deep learning provide opportunities to automate the disease detection process with improved accuracy and efficiency.

Artificial Intelligence (AI) is a computer science that studies how a system can imitate human intelligence or commonly called artificial intelligence [3]. Artificial intelligence has many branches of science, one of which is machine learning. Machine learning is a type of Artificial Intelligence (AI) that gives computers the ability to learn from data, without explicitly following programmed instructions [4]. Artificial intelligence-based leaf disease classification technology can help farmers in accelerating the process of identifying diseases that attack the leaves of grape plants, one of which is by using the Complex-Valued Neural Network (CVNN).

Technologies such as Complex-Valued Neural Network (CVNN) have advantages that are particularly relevant in the classification of grape leaf diseases. In a comparative study that included CNN and CV-CNN, CVNN was shown to be able to cope with complex image data, such as color and texture features in images [5]. The ability of the Complex-Valued Neural Network (CVNN) to efficiently combine and understand such features is an advantage in detecting small differences often found in grapevine diseases.

Experimental results also show that Complex-Valued Neural Network (CVNN) is able to outperform real-valued CNN models with higher accuracy [6]. In the context of grape leaf disease classification, increased accuracy is key to identifying and classifying diseases more precisely. In addition, the use of complex-valued data in grape leaf images that often have complex components would better suit the capabilities of a Complex-Valued Neural Network (CVNN). Thus, the Complex-Valued Neural Network (CVNN) can improve the model's ability to understand and process data that has both real and imaginary components that are usually difficult for conventional neural networks to cope with.

Various related studies that have been conducted previously for the classification of grape leaf diseases using CNN-VGG16 model image processing techniques by Hasan get 99.50%. The dataset used was 4000 images of grape leaves with four classes and 100 images from Google which were used as test data outside the dataset [7]. This study noted that the use of test images outside the dataset resulted in a lower accuracy rate (95%) compared to the test data in the dataset (97.25%). Complex-Valued Neural Network (CVNN) can utilize its ability to cope with complex data to improve the recognition accuracy of out-of-dataset images that may have greater variation [8].

Another study by Simanjuntak used the GLCM, Color Moment, and K*Tree methods [9]. The accuracy obtained in this study was 87.5%. The research dataset is divided into 150 images for training data and 100 images for test data. This research involves manual extraction of features such as Gray Level Co-Occurrence Matrix (GLCM) and Color Moment. Complex-Valued Neural Network (CVNN) has the ability to perform automatic feature extraction where the model can automatically recognize important features in the image, such as edges, texture, or color without requiring manual extraction [10].

This research implements the Complex-Valued Neural Network (CVNN) method and compares it with the Convolutional Neural Network (CNN) method in the context of grape leaf disease detection. By utilizing technology capable of handling complex image data, the Complex-Valued Neural Network (CVNN) has the potential to be an effective tool in accelerating and improving the accuracy of the grape leaf disease identification process. As such, this effort is expected to make a significant contribution to efficient vineyard management, increase agricultural productivity, and support economic growth in the agricultural sector.

2. RESEARCH METHOD

As a reference for conducting the research to achieve the expected objectives, the research methodology is carried out sequentially. The steps of this research are described using a research flow chart Figure 1 illustrates the stages of research that will be followed and serves as a comprehensive guide throughout the research process.

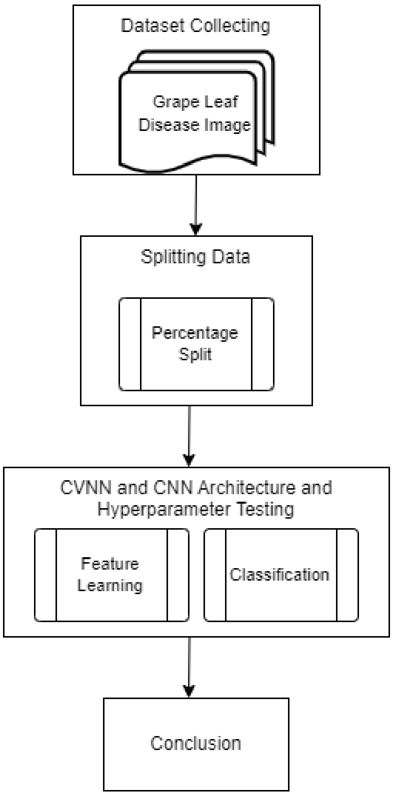


Figure 1. Digram of Research Method

2.1 Datasets Collecting

Researchers collected image data of grapevine diseases using secondary data as many as 100 images divided into 4 classes namely black rot, ESCA, leaf blight and healthy. Each class has 25 images in png format.

2.2 Data Splitting

At this step, the process of dividing data (split data) into training data and testing data is carried out. This process is a process to divide the data set that has previously been sorted and labelled. This process generally aims at training, and testing machine learning models. The data division method is carried out into two subsets, namely training data and test data using the percentage split method.

Percentage split is a commonly used approach in data processing and modelling [11]. In this method, the initial data is split by a certain percentage, where most of the data will be used to train the model (training data) and the rest will be used to test the performance of the model (testing data).

2.3 Complex-Valued Neural Network Model

Complex-Valued Neural Network (CVNN) is a type of neural network specifically designed to work with two-dimensional images. In image classification tasks, a Complex-Valued Neural Network (CVNN) considers an image as input, and this image is divided into one or more 2D matrices or image channels that are used as input in the object recognition or image classification process. This allows the network to understand the structure and characteristics of the image for tasks such as object recognition or image classification. One of the most important characteristics of a complex-valued neural network is its ability to process complex-valued information precisely [12]. Complex-Valued Neural Network (CVNN) can improve the model's ability to understand and process data that has both real and imaginary components, which is usually difficult for conventional neural networks to cope with.

In Complex-Valued Neural Network (CVNN) the inputs, weights, thresholds, and outputs are complex-valued. The input Un to the complex-valued neuron n is defined as follows [13]:

$$U_n = \sum_m W_{nm} X_m + T_n \quad (1)$$

With:

W_{nm} = the (complex-valued) weight connecting complex-valued neuron n with complex-valued neuron m

X_m = input (complex value) of complex value neuron m

T_n = threshold (complex value) of neuron n

The following is the architecture of the Complex-Valued Neural Network (CVNN) [14]:

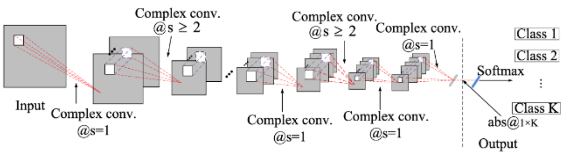
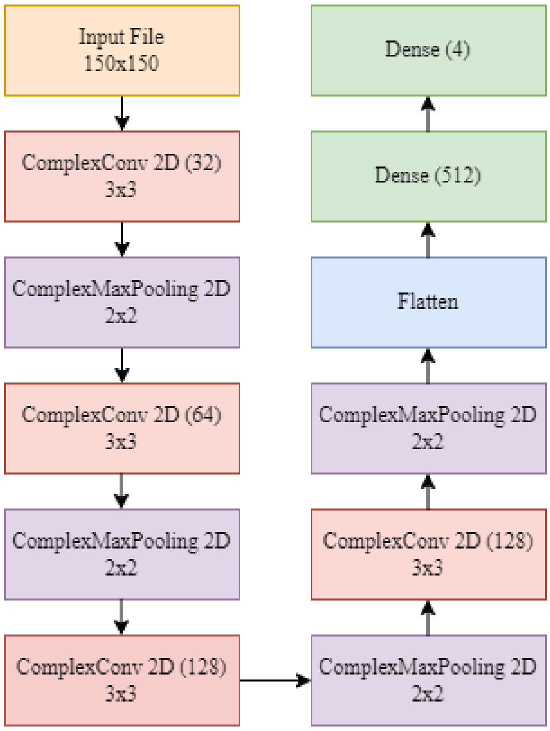


Figure 2. Complex-Valued Neural Network Architecture

Modelling is performed with the aim of producing feature extraction on data that has previously been trained based on data that has been organised into training data and test data. This process enables the Complex-Valued Neural Network (CVNN) model to learn intricate patterns and relationships within the image data, thereby enhancing its ability to generalize well to unseen instances during the testing phase.

This Complex-Valued Neural Network (CVNN) model consists of a complex convolution layer, complex polling, complex flattening layer, and a fully connected layer or dense layer as shown in Figure 3. The process in this Complex-Valued Neural Network (CVNN) model begins with an input image with a size of 150x150 pixels, the image will be processed at the convolution stage, and maxpolling this stage will be repeated 4 times before the data is processed at the flatten stage to change the shape of the array and the fully connected layer stage for the weight update process that occurs in the model. This process allows the model to adaptively adjust the feature representation required to distinguish between different grapevine disease classes, thereby improving classification accuracy. The following is an overview of the Complex-Valued Neural Network (CVNN) architecture used.

Figure 3. Layers of the CVNN Architecture



This research considers the setting of hyperparameter values such as epochs and the choice of optimizer as key factors in producing optimal model performance. Choosing the right optimizer has a significant impact on the speed of convergence and the quality of the resulting model. Therefore, in this study, two commonly used optimizers were selected, namely Stochastic Gradient Descent (SGD) and RMSprop.

SGD is a popular choice due to its simplicity and efficiency. It works by updating the model parameters based on the gradient of the selected random samples. As such, SGD is suitable for large datasets as it enables fast model learning and minimises computation time.

RMSprop was chosen for its ability to handle the problem of different learning rates for each parameter. It adaptively adjusts the learning rate for each parameter based on the gradient history, making it more effective in finding the optimum point in the parameter space. This makes RMSprop particularly suitable for datasets with varying scales or when the gradients of various features fluctuate significantly.

Using SGD and RMSprop as optimizers in scenarios of hyperparameter epoch values of 10, 30, 50, and 100, this study aims to gain a comprehensive understanding of how model performance evolves as epoch values vary, as well as how the two optimizers affect the convergence and quality of the resulting models. Additionally, by systematically exploring different combinations of optimizers and epoch values, this research seeks to identify the optimal configuration that maximises both accuracy and efficiency in grape leaf disease classification tasks.

2.3 Convolutional Neural Network Model

A neural network specifically designed to handle image processing problems. Convolutional neural network (CNN) is an effective method to classify, identify and recognise patterns in images. Convolutional neural network (CNN) is able to understand image details better because it has an architecture that matches the way the human brain processes visual information. The data used in Convolutional neural network (CNN) is two-dimensional data, such as images or sounds, and uses convolution operations in matrices and four-dimensional weights which are a set of convolution kernels. With the nature of the convolution process, Convolutional neural network (CNN) can only be used on data that has a two-dimensional data structure [15]. The following is the architecture of the Convolutional Neural Network (CNN) [16]:

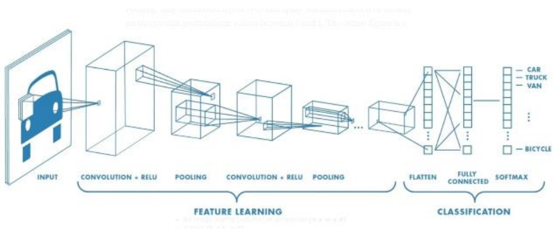


Figure 4. Convolutional Neural Network Architecture

3. RESULT AND DISCUSSION

3. 1 Dataset

The dataset used was taken from Surabaya Grapes which is a demonstration plantation in the Surabaya area. The data used were 100 images with 4 classes consisting of 25 images from each class. The following is an example of the data used:

Table 1. Datasets

No	Name	Grape Leaf	Number of Sample
1	Black Rot		25
2	Esca		25
3	Leaf Blight		25
4	Healthy		25

The data collection procedure was conducted by directly photographing the leaves, thereby enhancing the representativeness of the entire dataset. Furthermore, the dataset is partitioned into separate training and test subsets to facilitate training the model practically and evaluating its performance accurately. These datasets may include variations in image quality, lighting conditions, and orientation, which pose challenges for the model to demonstrate performance and adaptability across different situations.

3. 2 Complex-Valued Neural Network and Convolutinal Neural Network Experiments

The following is a scenario of experiments conducted in this research. Experiments carried out include data division, image input, epoch and batch size used. This scenario is used in the Complex-Valued Neural Network (CVNN) and Convolutional Neural Network (CNN) models:

Table 2. Experiment Scenario

Dataset Type	Description
Data splitting	80% data train and 20% data test
Input image	150 x 150
Epoch	10, 30, 50, and 100
Batch size	10
Class	4 class

Table 2 presents information related to the datasets used in research or experiments related to the classification of grape leaf disease images. Data division is done by using 80% of the total dataset as training data to train the model, while the remaining 20% is used as test data to test the performance of the trained model. The image used has a size of 150 x 150 pixels, which is the standard dimension in image processing. In addition, the model training process is performed with a varying number of iterations or epochs, namely 10, 30, 50, and 100, which indicates the number of times the entire dataset is used to train the model. The batch size, which is the number of data samples processed in one training iteration, was set at 10. The dataset consists of four classes or categories that represent the different types of grape leaf diseases to be classified. Here is the summary of the Complex-Valued Neural Network model.

```
Layer (type)                Output Shape              Param #
=================================================================
complex_conv2d (ComplexCon  (None, 148, 148, 32)      896
v2D)

complex_max_pooling2d (Com  (None, 74, 74, 32)        0
plexMaxPooling2D)

complex_conv2d_1 (ComplexC  (None, 72, 72, 64)        18496
onv2D)

complex_max_pooling2d_1 (C  (None, 36, 36, 64)        0
omplexMaxPooling2D)

complex_conv2d_2 (ComplexC  (None, 34, 34, 128)       73856
onv2D)

complex_max_pooling2d_2 (C  (None, 17, 17, 128)       0
omplexMaxPooling2D)

complex_conv2d_3 (ComplexC  (None, 15, 15, 128)       147584
onv2D)

complex_max_pooling2d_3 (C  (None, 7, 7, 128)         0
omplexMaxPooling2D)

complex_flatten (ComplexFl  (None, 6272)              0
atten)

complex_dense (ComplexDens  (None, 512)               3211776
e)

complex_dense_1 (ComplexDe  (None, 4)                 2052
nse)

=================================================================
Total params: 3454660 (13.18 MB)
Trainable params: 3454660 (13.18 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 5. Summary of CVNN Model

The Complex-Valued Neural Network (CVNN) model used is a neural network model that is arranged sequentially, meaning that each layer is connected sequentially. The model consists of different types of layers that are useful for processing complex image data. Firstly, there is the ComplexConv2D layer that uses 32 filters with a kernel size of (3,3) and uses the ReLU activation function. The input image is expected to have dimensions of (150, 150, 3), which indicates an image of 150x150 pixels with 3 colour channels (RGB). Next, the ComplexMaxPooling2D layer is used to reduce the image dimension by selecting the maximum value in a window of size (2,2). This process continues with the addition of a complex convolution layer and a complex max pooling layer successively, each with increasing filter complexity. After a series of convolution and max pooling layers, the result is flattened using the ComplexFlatten layer to produce a one-dimensional vector. This vector is then connected to a fully connected ComplexDense layer consisting of 512 neurons with a ReLU activation function. A ComplexDense layer with 4 neurons and a softmax activation function is used to generate the classification output, where each neuron represents the prediction probability for each of the four classes in the grape leaf disease image classification.

The Convolutional Neural Network (CNN) model used has several layers. Firstly, the Conv2D layer is used to convolve the input image using 32 filters with kernel size (3,3) and ReLU activation function. The MaxPooling2D layer is then used to reduce the image dimension by selecting the maximum value in a window of size (2,2). This process is repeated by adding Conv2D and MaxPooling2D layers, with increasing filter complexity at each convolution layer. After that, the final convolution result is flattened into a one-dimensional vector using the Flatten layer, so that it can be connected to the fully connected layer. The first Dense layer with 512 neurons and ReLU activation function is used to process the input vector. Finally, the last Dense layer with 4 neurons and activation function softmax produces the classification output, where each neuron represents the prediction probability for each of the four classes in the image classification. Here is the summary of the Convolutional Neural Network model.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 32)      896

 max_pooling2d (MaxPooling2  (None, 74, 74, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 72, 72, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 36, 36, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 17, 17, 128)       0
 g2D)

 conv2d_3 (Conv2D)           (None, 15, 15, 128)       147584

 max_pooling2d_3 (MaxPoolin  (None, 7, 7, 128)         0
 g2D)

 flatten (Flatten)           (None, 6272)              0

 dense (Dense)               (None, 512)               3211776

 dense_1 (Dense)             (None, 4)                 2052

=================================================================
Total params: 3454660 (13.18 MB)
Trainable params: 3454660 (13.18 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 6. Summary of CNN Model

3.3 Model Analysis

After the experiments that have been carried out, the accuracy of the Complex-Valued Neural Network (CVNN) model is obtained. The following table compares the accuracy of the CVNN model:

Table 3. Comparison of accuracy and loss on train, val, and test data of CVNN model

Epo-ch	Opti-mizer	Train		Val		Test	
		Acc	Loss	Acc	Loss	Acc	Loss
10	SGD	0.65	0.91	0.62	0.95	0.56	1.02
	RMS-prop	0.81	0.49	0.79	0.53	0.75	0.59
30	SGD	0.85	0.35	0.79	0.49	0.69	0.53
	RMS-prop	0.94	0.18	0.89	0.36	0.83	0.52
50	SGD	0.92	0.21	0.87	0.36	0.87	0.38
	RMS-prop	0.99	0.01	0.85	0.89	0.89	0.48
100	SGD	0.97	0.06	0.85	0.34	0.86	0.36
	RMS-prop	**1.0**	**0.002**	**0.89**	**0.69**	**0.97**	**0.26**
Average		0.89	0.27	0.81	0.57	0.80	0.51

The following table compares the accuracy results of CNN model experiments:

Table 4. Comparison of accuracy and loss on train, val, and test data of CNN model

Epoch	Optimizer	Train		Val		Test	
		Acc	Loss	Acc	Loss	Acc	Loss
10	SGD	0.71	1.02	0.60	1.04	0.58	1.09
	RMSprop	0.79	0.46	0.78	0.58	0.66	0.63
30	SGD	0.77	0.49	0.73	0.73	0.67	0.74
	RMSprop	0.94	0.15	0.93	0.31	0.82	0.46
50	SGD	0.82	0.39	0.78	0.56	0.76	0.51
	RMSprop	**0.97**	**0.07**	**0.87**	**0.58**	**0.89**	**0.67**
100	SGD	0.98	0.07	0.78	0.46	0.88	0.24
	RMSprop	0.96	0.14	0.90	0.64	0.80	0.97
Average		0.86	0.34	0.79	0.61	0.75	0.66

In Table 3 comparing the performance of the Complex-Valued Neural Network (CVNN) model, it is noteworthy that the utilization of the RMSprop optimizer with 100 epochs yielded the highest accuracy. Specifically, on the training dataset, this model attained a remarkable accuracy of 100% accompanied by a negligible loss of 0.002. While on validation data, the Complex-Valued Neural Network (CVNN) achieved an accuracy of 89% with a loss of 0.68. In the last evaluation stage, when tested using test data, this model is still able to maintain excellent performance with an accuracy of 97% and a loss of 0.27.

In Table 4 comparison of Convolutional Neural Network (CNN) models, the RMSprop optimizer with epoch 50 shows the highest performance with accuracy on train data of 97% and loss of 0.07. While the validation data achieved an accuracy of 87% and a loss of 0.58. In the testing phase using test data, it achieved an accuracy of 89% with a loss of 0.67.

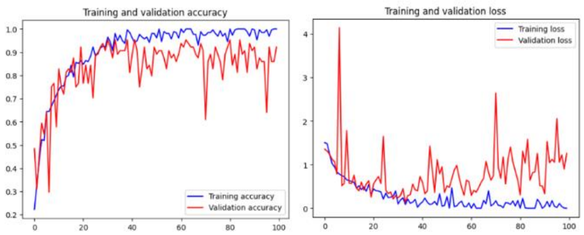


Figure 7. CVNN Model Evaluation Graph

Figure 7 is an evaluation graph depicting the training and validation accuracy as well as the training and validation loss of the Complex-Valued Neural Network (CVNN) model using the RMSprop optimizer with 100 epochs which provides a clearer visual representation of how the model's performance evolves with the training and validation process.

Figure 8 is an evaluation graph that illustrates the training and validation accuracy and training and validation loss of the Convolutional Neural Network (CNN) model using the RMSprop optimizer with an epoch of 50.

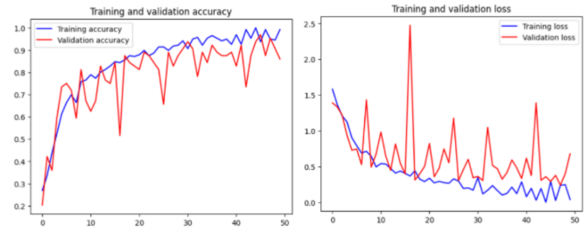


Figure 8. CNN Model Evaluation Graph

4. CONCLUSION

Based on the results of the research conducted, it can be concluded that the Complex-Valued Neural Network (CVNN) model shows superior performance compared to the Convolutional Neural Network (CNN) in classifying grape leaf disease images. Using the RMSprop optimizer for 100 epochs on the CVNN model shows the best configuration by achieving the highest accuracy on training (100%), validation (89%), and test (97%) data, as well as low loss on each dataset. This research emphasises the important role of optimizer selection and training duration in optimising model performance. However, while the Complex-Valued Neural Network (CVNN) is capable of delivering impressive results, there are issues to be aware of, namely that there are values where accuracy is high but loss is also high. Therefore, maximising the potential of the Complex-Valued Neural Network (CVNN) in image classification applications requires proper hyperparameter adjustment.

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