SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 4, October 2023
DOI : https://doi.org/10.33395/sinkron.v8i4.12949
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Satellite Images Classification using MobileNet V-2 Algorithm

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Submitted : Aug 30, 2023 | **Accepted** : Sep 1, 2023 | **Published** : Oct 1, 2023

Abstract: Satellite imagery is an invaluable source of visual information for environmental monitoring and land mapping with high resolution and wide coverage. In this modern technological era, advances in Deep Learning technology have brought great benefits in utilizing satellite images for various purposes. One of the efficient Deep Learning models for satellite image classification is MobileNet V-2, which is specifically designed for devices with limited resources such as smartphones. This study aims to develop an accurate satellite image classification model using Convolutional Neural Network algorithm and MobileNet V-2 model. The data used is taken from the RSI-CB256 dataset developed through crowdsourcing data. This research resulted in the performance of three deep learning models, namely ResNet50, MobileNet V-2, and VGG-16. ResNet50 is the highest model performed best during the training phase, achieve an accuracy of 98.40%. MobileNet V-2 and VGG-16 followed with 95.64% and 96.62% accuracy, respectively. The evaluation results demonstrate the model's strong ability to accurately classify satellite imagery and strengthen the model's ability to generalize well. With high accuracy and the ability to run on smartphone devices, this model has the potential to provide valuable information for governments and scientists in preserving the earth and better responding to environmental changes.

Keywords: Satellite Images; RSI-CB256 Dataset; Classification; Object Recognition; MobileNet V-2;

INTRODUCTION

In an era of rapid development of information technology, satellite imagery has become a very valuable source of data in various fields. Satellite imagery provides visual information about the Earth's surface with high resolution and wide coverage. These advantages make satellite imagery an irreplaceable tool in national defense (Hadyanti & Rudiawan, 2022), mapping environmental monitoring, natural resource management, climate change monitoring, and more. The utilization of satellite imagery with machine learning algorithms that learn like humans has brought great benefits in various fields. (Firmansyah et al, 2019) showed that in mangrove forest monitoring, satellite imagery can be utilized together with the Support Vector Machine (SVM) machine learning algorithm. Other fields also use satellite imagery and machine learning to learn.

MobileNet is a CNN architecture model developed specifically for use on devices with limited computational resources, such as smartphones. In relation to the problem of satellite image classification, (Prioko et al, 2019) demonstrated smoke classification in satellite images using the MobileNet V-2 model, this research develops a system that is expected to classify smoke images in satellite images using the Convolutional Neural Network using the USTC SmokeRS dataset which totals

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6225 images and is separated into 6 classes and achieved an accuracy of 83%. The dataset used in this research was obtained from Li et al., who conducted research on RSI-CB (Remote Sensing Image Classification Benchmark) using crowdsourcing methods to build a dataset called RSI-CB256. (D. Yu et al, 2020) propose the CNN method using the mobileNet V2 architecture to extract deep and abstract image features, this study used three data sets: UC Merced, AID, and NWPU-RESISC45. The proposed method has fewer parameters and calculations, and achieves higher accuracy. (Firmansyah et al, 2019) compare SVM and Decision Tree classifications for object-based mangrove mapping using Sentinel-2B satellite imagery on Gili Sulat, East Lombok, the classification of satellite images with SVM produces 95% accuracy to predict 1 class related to the presence or absence of mangrove forests. Futhermore, (Magdalena et al, 2021) demonstrating a satellite image classification through SPOT-6 Satellite Imagery with CNN produces 95.45% accuracy to predict 1 class related to whether or not a land is vegetated.

Taking into account these previous studies, this research takes a further step by developing a satellite image classification model using MobileNet V-2 to classify not just one object, but four objects on stellite imagery. The four objects include water area, green area, deserts area, and clouds area. In addition, this research will also try to improve accuracy by preprocessing with the Data Augmentation method which makes the training process with little data can produce maximum accuracy. The contribution of this research lies in the application of MobileNet V-2 in the context of satellite image classification and the use of appropriate preprocessing methods to produce high accuracy even for predicting 4 classes. In this research, the classification process of satellite images is carried out with the Convolutional Neural Network algorithm and a pretrained model called MobileNet V-2, the purpose of this research is to develop an accurate and effective classification model in identifying satellite images. The research results focus on producing high accuracy so that it can help in various applications, such as environmental mapping, natural resource management, and natural disaster monitoring.

LITERATURE REVIEW

Satellite Images

Satellite imagery is an image taken from a satellite revolving around the Earth. The satellite is equipped with sensors that can capture images from a high altitude. Satellite imagery has a high resolution and is able to map various aspects of the Earth's surface, such as land, oceans, and trees. Satellite imagery is very useful in a variety of applications, such as environmental monitoring, area mapping, and natural disaster monitoring (Hadyanti & Rudiawan, 2022).

MobileNet V-2

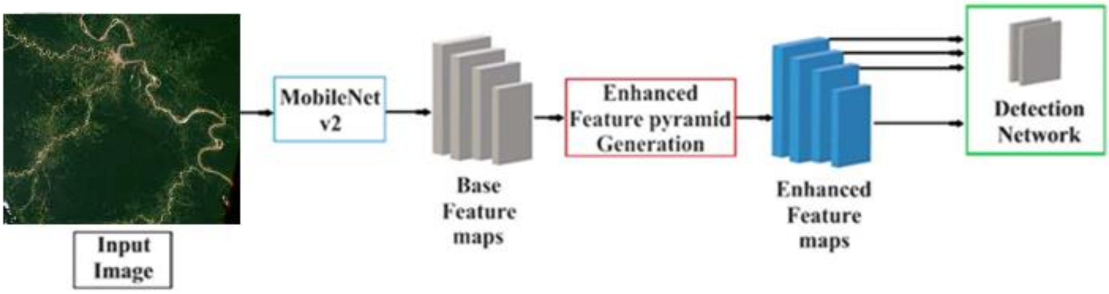

Figure 1. MobileNet V-2 Architecture Illustration

MobileNet V-2 Architecture Illustration can be seen in Figure 1, MobileNetV2 is an efficient and lightweight deep neural network architecture. It is an improvement on the original MobileNetV1 model with several important changes designed to enhance efficiency and performance, especially on mobile and embedded vision applications. The structure of MobileNetV2 is based on an inverted residual structure where the shortcut connections are between the thin bottleneck layers (Yu et al, 2020).

MobileNetV2, like its predecessor, uses depthwise separable convolutions as efficient building blocks. These convolutions divide a standard convolution into a depthwise convolution and a pointwise

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convolution, thus reducing computational complexity and model size. Inverted residuals and linear bottlenecks is a novel feature introduced in MobileNetV2. Traditional residual blocks have input and output dimensions equal and use bottlenecks to reduce computation. In the inverted residual structure, the layer first expands the dimension to a much larger size, does a depthwise convolution, then projects it back to a lower dimension. This results in less information loss during the bottleneck operation. Shortcut connections are used between the bottleneck layers to preserve the previous features, enabling the reuse of these features in subsequent layers. This aids in improving the efficiency of the network and contributes to the better performance.

Benefits of MobileNet V2 for Satellite Image Classification is highly efficient in terms of computation and size, making it suitable for applications where resources are constrained, for example, in real-time satellite image analysis systems (Choi & Sobelman, 2020). Despite its efficiency, MobileNetV2 does not compromise much on accuracy. It performs on par with much larger and computationally expensive models on several benchmarks. For satellite image classification, where diverse features need to be recognized, this is a major advantage (Song et al, 2023). MobileNet V2 can be effectively used as a feature extractor in a transfer learning setting. Given that large-scale labeled satellite image data may be difficult to come by, using a pre-trained MobileNetV2 model and fine-tuning it on the specific task can boost performance and reduce training time (Xiang, 2023). The architecture of MobileNet V2 is structured in a way that it can be easily scaled up or down based on the computational resources available. This makes it adaptable for different levels of satellite image resolution and system resource requirements (Burra, 2022). MobileNetV2 is designed to be robust to a range of input sizes, which makes it flexible and a good fit for tasks like satellite image classification, where the input images can vary greatly in terms of size and resolution (Tazin et al, 2021).

The efficient yet powerful MobileNetV2 is well-suited for satellite image classification tasks, offering a good balance between accuracy and computational resources. Its features like inverted residuals, linear bottlenecks, and depthwise separable convolutions make it a promising model for this kind of task.

After training the MobileNet v2 model to classify satellite images with Training and Validation Data. The Testing process will be executed to test the trained MobileNet V-2 model to predict the Test Data. Accuracy formula will be used to measure this stage (Grandini *et al*, 2020). The formula is as follows in number 1:

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \qquad (1)$$

With known:
- TP = True Positive
- TN = True Negative
- FN = False Negative
- FP = False Positive

Then the Loss formula (Muthukumar *et al*, 2021) to measure the mistakes made by MobileNet V-2 is as follows in number 2:

$$L(y,\hat{y}) = -\sum_{i=1}^{C} y_1 \, log(\hat{y}_i) \qquad (2)$$

With known:
- L = loss function
- y = true label vector in one-hot encoding form
- ŷ = prediction vector issued by the model
- C = total number of classes
- i = class index
- log = natural logarithm

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METHOD

In conducting research, there are several stages carried out by researchers. The flow of these stages can be seen in Figure 2.

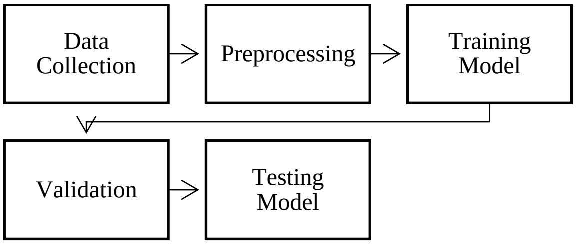

Figure 2. Research Stages

Data Collection

In this research, there is a collection of data in the form of the RSI-CB256 Satellite Image Dataset which will be used for the research process. The dataset used in this research is the Remote Sensing Image Classification Benchmark RSI-CB on https://github.com/lehaifeng/RSI-CB. This dataset is built using data from various satellite image sources collected online (Liu et al., 2022). The description of the dataset is in Table 1. below:

Table 1. Dataset description

Satellite Image Dataset Attributes	Description
Independent Variable	Satellite Images
Dependent Variable	Types of satellite images (ocean, meadow, desert, and cloud)
Size	256x256 px
Number of Data Examined	178

The following Figure is a view of the satellite image in data collected and used to train the MobileNet V-2 model to classify satellite image types.

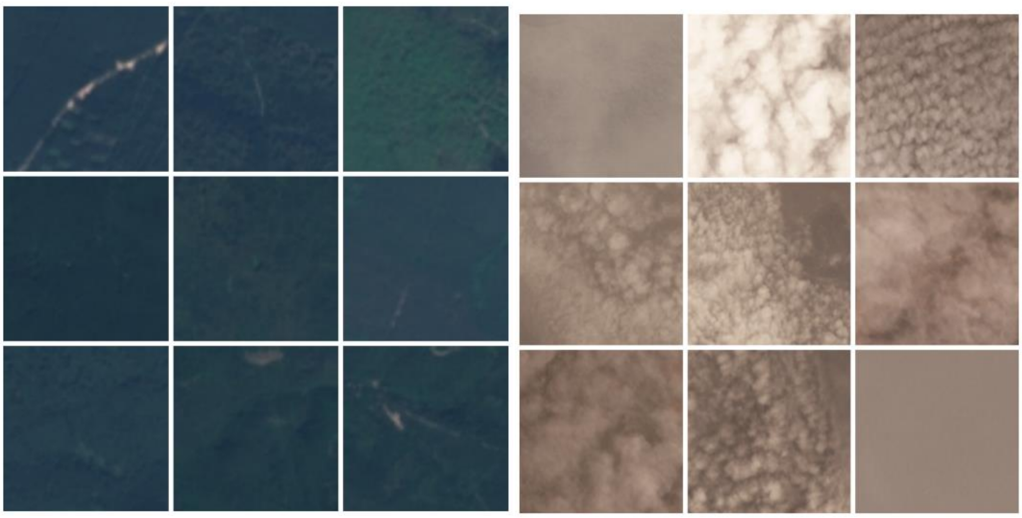

Figure 3. Sample Satellite Images (Green Area and Cloud Area)

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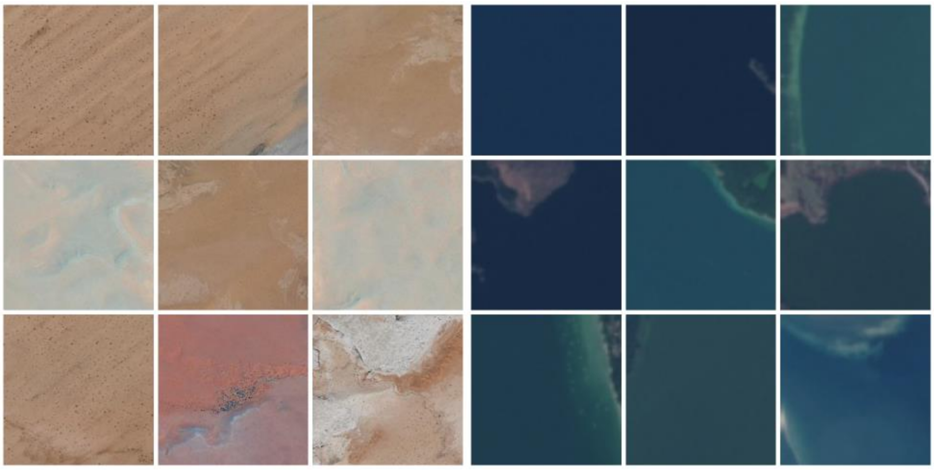

Figure 4. Sample Satellite Images (Desert Area and Water Area)

Preprocessing

At this stage the data will be processed before being processed by MobileNet V-2. The image size will be adjusted to be consistent, then Data Augmentation techniques will be used to change the image so that the model can study the data more accurately. The data sharing process is carried out with a ratio of 70% Training Data, 20% Validation Data, and 10% Test Data.

Then the preprocessing stage with the Data Augmentation technique is carried out using the following parameters in Table 2:

Table 2. Data Augmentation Technique

Preprocessing Type	Process Implemented
rescale = 1./255	Changes the image pixel values from a range of 0-255 to a range of 0-1. This helps in speeding up the training process and makes convergence faster.
shear_range = 0.2	Performing a shear operation on the image, which is shifting parts of the image to create a distortion effect. A value of 0.2 means the shear intensity is between -0.2 to 0.2.
zoom_range = 0.2	Performs a zoom operation on the image. A value of 0.2 means that the image can be zoomed in or out between 80% to 120% of the original size.
horizontal_flip = True	Performs horizontal flipping of the image. This means the image can be rotated 180 degrees along the y-axis

After Data Augmentation, the size and batch size are determined with the following parameters in Table3:

Table 3. Size and Batch Size

Size	Description
target_size = (224, 224)	Each image read will be resized to 224x224 pixels.
batch_size = 32	The model will take 32 image samples at each training iteration.

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Finally, the data division process was performed and resulted in the following amount of data:

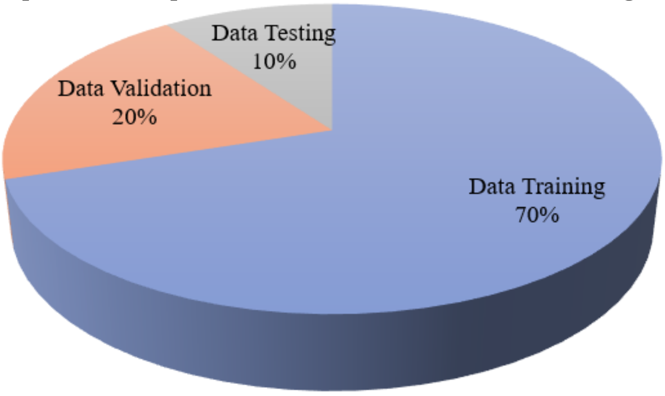

Figure 5. Dataset Division

Dataset division is done by dividing the data into three parts: 10% testing data, 20% validation data, and 70% training data. Before the training process begins, the images in the dataset undergo transformation. First, the pixel values of the images are changed from a range of 0-255 to a range of 0-1 with rescale = 1./255. This aims to speed up the training and make the model convergence faster. Next, a shear operation is performed on the image with a value of shear_range = 0.2, which shifts parts of the image to create a distortion effect with an intensity between -0.2 to 0.2. Then, a zoom operation is performed on the image with a value of zoom_range = 0.2, which allows the image to be zoomed in or zoomed out between 80% to 120% of the original size. In addition, horizontal flipping of the image is performed with horizontal_flip = True, which allows the image to be rotated 180 degrees along the y-axis. Finally, each image was read to a size of 224x224 pixels (target_size = (224, 224)) for use in the model. The model training process is performed by taking 32 image samples at each iteration with batch_size = 32. This batch size helps to speed up the training and optimize the use of computational resources.

After collecting the satellite images data, the subsequent phase involves formulating a classification model.. The initial step encompasses training the data using a designated training dataset, followed by employing a distinct testing dataset to generate predictive outcomes, subsequently quantifying the resultant accuracy. The hyperparameters employed in this investigation are outlined as follows.

Table 4. Hyperparameter Summary

Hyperparameter	**Value**
*input*_shape	(image_width, image_height, 3)
include_top	False
weights	None
layer.trainable	False
layers.Dense	1024 units, 'relu' activation
layers.Dropout	0.2
layers.Dense (*output* layer)	1 unit, 'sigmoid' activation
optimizer	Adam(0.0001)
loss	'categorycal_crossentropy'
metrics	'accuracy'

Explanations of hyperparameters :

1) Input_shape = (image_width, image_height, 3): This hyperparameter defines the form of the input entered into the model. In this case, the input form are the image width, image height, and the number of color channels (RGB). Input shapeit is important to adjust to the dataset used.

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2) Include_top = False: This hyperparameter is used to determine whether we want to include or not the topmost classification layer in the mode have been trained before. In this case, we're excluding layers because we're going to be adding our own custom layer.
3) Weights = None: Since we will load the weights from a local file, we initialize them model weight as None
4) Layer.trainable = False: After loading the weights from the local file, we freeze layers of a pre-trained model. This means that the weights are on this layer will not be updated during the training process.
5) Layers.Dense(1024, activation='relu'): Adds a fully connected layer (Dense) with 1024 hidden units and ReLsU activation function.
6) Layers.Dropout(0.2): Dropout is a regularization technique in which multiple nodeshe inner layer is removed randomly with the aim of avoiding overfitting. In In this case, we use a dropout rate of 0.2.
7) Layers.Dense(1, activation='sigmoid'): Adds an output layer for binary classification. Since this is a binary classification, we only need one output unit with sigmoid activation function.
8) Optimizer = Adam(learning_rate=0.0001): Adam optimizer works by taking advantage of the advantages of AdaGrad which is to maintain per-parameter learning that has the effect of improving model performance.. We using a learning rate of 0.0001
9) Loss = 'categorycal_crossentropy': Since this is a binary classification problem, we using categorycal cross entropy as the loss function.
10) Metrics = ['accuracy']: The metrics used to evaluate the model

Training Model and Validation

At this Stage train model to classify satellite images with Training and Validation Data performance.

Testing

At this stage, the testing process is carried out by testing the model that has been trained and validated and then tested with Test Data. Evaluation in the form of accuracy calculations is the final part in this stage, the jupyter notebook program that has been created will produce output in the form of evaluation results of the Confusion Matrix prediction truth table and its accuracy with the accuracy formula (2).

RESULT

In this section, we will explain the steps taken to obtain satellite image classification results in this study using three different models, namely MobileNet V2, VGG-16, and ResNet-50. The first stage is the collection of satellite image datasets that include various categories or classes to be classified. Next, the dataset will be divided into training data, validation data, and testing data to train, optimise, and test the performance of each model. After that, data pre-processing is performed, including image transformation, rescale, and batch division to prepare the data to match the input expected by the model. Next, the MobileNet V2, VGG-16, and ResNet-50 models will be initialised and trained using the pre-processed training data. During training, the model weights and parameters will be adjusted and updated repeatedly to improve performance. Once training is complete, the models will be tested on test data to evaluate classification accuracy and reliability.

The results of the three models will be compared to determine the most effective model in classifying the satellite images in this study. This process will provide a deeper understanding of the potential use of these models in environmental monitoring applications, land mapping, and other fields that require accurate and efficient analysis of satellite imagery.

The following Table 5 are the training results of the three models. The display of the prediction success results on the Validation Data of the three models is displayed in the Confusion Matrix table as in the following table. The output display in the programme can be seen in the appendix section of this research report.

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Table 5. Training Results of the Three Models with Validation Data

	Prediction / Actual	Green Area	Cloud	Dessert	Water
MobileNet V-2	Green Area	274	15	7	4
	Cloud	0	226	0	0
	Dessert	0	0	286	14
	Water	5	0	4	291
VGG-16	Green Area	295	2	0	3
	Cloud	23	203	0	0
	Dessert	0	0	298	2
	Water	2	1	5	292
ResNet50	Green Area	299	0	0	1
	Cloud	2	224	0	0
	Dessert	0	0	292	8
	Water	2	0	5	293

The table above is the performance evaluation result of three classification models on validation data, namely MobileNet V-2, VGG-16, and ResNet50, in classifying four types of images: Green Area, Clouds, Desert, and Water. The following is an explanation of the evaluation results for each model. In a study that predicts 4 classes, the confusion matrix will have more than one TP, TN, FP, and FN for each class, not just one set for all classes. there are only two results: correct prediction and incorrect prediction.

1. Correct Prediction in this satellite classification research occur when the predicted class (column) matches the actual class (row). for example, when "cloud" is predicted and the actual is also "cloud". MobileNet V-2 has 1077 correct predictions, VGG-16 has 1088 correct predictions, while ResNet-50 has 1108 correct predictions.
2. Incorrect predictions are when the predicted class does not match the actual class, like when "cloud" is predicted but the actual is "desert" or any other classes. MobileNet V-2 has 49 incorrect predictions, VGG-16 has 38 incorrect predictions, while ResNet-50 has 18 incorrect predictions.

The following Table 6. are the training results of the three models. The display of the prediction success results on the Test Data of the three models is displayed in the Confusion Matrix table as in the following table. The output display in the programme can be seen in the appendix section of this research report.

Table 6. Testing Results of the Three Models with Validation Data

	Prediction / Actual	Green Area	Cloud	Dessert	Water
MobileNet V-2	Green Area	128	15	6	1
	Cloud	0	114	0	0
	Dessert	0	0	148	14
	Water	0	0	1	149
VGG-16	Green Area	149	0	0	1
	Cloud	9	105	0	0
	Dessert	0	0	150	0
	Water	0	0	1	149
ResNet50	Green Area	150	0	0	0
	Cloud	2	112	0	0
	Dessert	0	0	147	8
	Water	1	0	0	149

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In a study that predicts 4 classes, the confusion matrix will have more than one TP, TN, FP, and FN for each class, not just one set for all classes. Thus there are only two results i.e. correct prediction and incorrect prediction

1. Correct Prediction in this satellite classification research occur when the predicted class (column) matches the actual class (row). for example, when "cloud" is predicted and the actual is also "cloud". MobileNet V-2 has 539 correct predictions, VGG-16 has 553 correct predictions, while ResNet-50 has 558 correct predictions.
2. Incorrect predictions are when the predicted class does not match the actual class, like when "cloud" is predicted but the actual is "desert" or any other classes. MobileNet V-2 has 37 incorrect predictions, VGG-16 has 11 incorrect predictions, while ResNet-50 has 11 incorrect predictions.

In the training stage, the accuracy calculation results show that the three models performed very well with high accuracy rates. The ResNet50 model recorded the highest accuracy of 92.33%, while MobileNet V-2 with 89.75%, and VGG-16 with 90.67%, respectively. These results show in Table 7. that all three models have a strong ability to accurately classify satellite images.

Table 7. Training Stage Accuracy Calculation Results with Validation Data

Model Name	**Total Correct Prediction (TP+TN)**	**Total Predictions (TP+TN+FP+FN))**	**Accuracy (%)**
MobileNet V-2	1077	1200	89.75
VGG-16	1088	1200	90.67
ResNet50	1108	1200	92.33

Meanwhile, in the testing stage as shown in Table 8, the evaluation results show that the three models perform very well with high accuracy. ResNet50 recorded the highest accuracy of 98.94%, followed by MobileNet V-2 with 95.57%, and VGG-16 with 98.05%. This indicates that in Table 8. All three models were able to perform very accurate classification, with ResNet50 being the best model in terms of accuracy.

Table 8. Testing Results Accuracy of Testing Stage with Test Data

Model Name	**Total Correct Prediction (TP+TN)**	**Total Predictions (TP+TN+FP+FN))**	**Accuracy (%)**
MobileNet V-2	539	564	95.57
VGG-16	553	564	98.05
ResNet50	558	569	98.94

DISCUSSIONS

Furthermore, based on this research, the advantages and disadvantages of each model are obtained:

a. MobileNet V-2

MobileNet V-2 has a high accuracy of 95.57% and computational efficiency with a relatively small number of parameters, making it suitable for devices with limited resources. However, this model may lack the ability to recognise highly complex patterns on highly diverse datasets.

b. VGG-16

VGG-16 has a strong ability to describe complex features of images and is suitable for classification tasks that require a deeper understanding of visual features. However, its main drawback is computationally expensive due to its deep architecture with many layers.

c. ResNet50

ResNet50 stands out with a high accuracy of 98.94% and good training capabilities with the ResNet architecture. However, the drawback of ResNet50 lies in the complexity of the architecture which can be complicated to understand and configure. The selection of the best model should consider the specific needs of the project or application as well as the available resources to obtain optimal performance in the classification task.

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CONCLUSION

This research successfully tried to use three different models to classify satellite images. Based on the results of validation tests and trials with test data, ResNet50 recorded the highest accuracy of 98.94%, followed by MobileNet V-2 with 95.57%, and VGG-16 with 98.05%. This high accuracy indicates the ability of the three models to perform classification very accurately. Therefore, for the classification task in this study, ResNet50 is the best model in terms of accuracy. all models tested in this study performed very well in classification. Although MobileNet V-2 has successfully achieved high accuracy, further research can be done by examining other models or datasets that might support the development of research in the field of satellite classification. For more comprehensive environmental monitoring, research can be focussed on using multitemporal satellite imagery data.

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