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Integration of Thermal Images and Agricultural Data for Multi-Class Classification of Palm Seed Origin using MobileNet

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Abstract

This research develops a palm kernel origin classification model by combining thermal images and numerical agricultural data using MobileNet architecture. The quality of palm kernels is highly influenced by origin and environmental conditions, but manual visual identification is difficult. Therefore, a machine learning-based approach is applied to improve classification accuracy. The dataset consists of 7.257 thermal images representing 73 seed origin classes, as well as supporting data in the form of soil, fruit, and socioeconomic information collected from plantations in Aceh, Indonesia. The MobileNet model was tested in two scenarios: using only thermal images, as well as a combination of thermal images with agricultural data. Results show that data integration provides significant performance improvement. The best model was obtained from MobileNet V3-Large with the optimal hyperparameter configuration (batch size 16, learning rate 0.001, and optimizer Adam), resulting in test accuracy of 99.04%, validation 97.25%, and training 98.77%. This finding opens up opportunities for the application of real-time classification technology in the plantation environment, especially to support precision and sustainable agriculture.

Keywords : *Hyperparameter tuning, MobileNet, Palm seed classification, Precision agriculture.*

1. INTRODUCTION

Palm oil is one of the main commodities in Indonesia's agricultural sector that contributes significantly to the national economy [1]. Based on data from Badan Pusat Statistik (BPS) Indonesia, palm oil production in 2023 reached 47.084 million tons, an increase of 0.57% compared to the previous year. Riau Province contributed the highest production of 19.59% followed by Central Kalimantan at 17.98%, West Kalimantan at 11.05%, North Sumatra at 10.63%, South Sumatra at 8.77%, and the rest came from other provinces [2]. Palm kernels from superior plants are the main component in the palm oil production process which is Indonesia's export commodity [3].

The quality of palm kernels is strongly influenced by the origin of the seed and the environmental conditions in which it grows. Environmental factors such as soil type and climatic elements (temperature, humidity, rainfall, duration of irradiation, and wind speed) play a significant role in determining the quality of plant growth [4][5]. Therefore, the ability to classify the origin of palm kernels based on the region of origin is important to improve production quality. However, visually identifying the origin of palm kernels is difficult for humans because there are no clear visible differences in the kernels. Therefore, a technology-based approach is needed to classify seed origin more accurately and efficiently.

Advances in image processing and machine learning technologies offer a solution to this challenge. In particular, the application of thermal imaging enables the detection of unique characteristics in palm kernels that are not visible in regular visual imagery. Thermal cameras work by detecting infrared radiation based on the surface temperature of the object without the need for external

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lighting [6]. This provides the advantages of stable image quality and the ability to reveal internal information, making it ideal for field applications.

To overcome the limitations of visual classification of oil palm fruits, Zolfagharnassab et al. (2022) utilized thermal images based on the difference between fruit surface temperature and ambient temperature. Various classification methods were applied, and the best results were obtained from Artificial Neural Network (ANN) with test accuracy reaching 92.5% [7]. In addition, a study by Elfatimi et al. (2022) showed the success of MobileNet architecture in the classification of plant leaf diseases, especially in bean leaves with image datasets. The study trained and compared MobileNet and MobileNetV2 and obtained a test accuracy of 92.97% [8]. This study confirms that lightweight CNN models such as MobileNet are very effective in the context of image-based classification in plants.

In addition to visual information from thermal images, the integration of agricultural data can add information that can improve productivity in agriculture [9]. As explained by Showkat Ahmad Bhat and Nen-Fu Huang, the application of Big Data and Artificial Intelligence (AI) has revolutionized precision agriculture by enabling large-scale data analysis that supports more accurate decision making [10]. In this context, the utilization of Convolutional Neural Network (CNN) architectures such as MobileNet is an ideal choice as they are efficient, lightweight, and can be implemented on devices with limited resources including smartphones that enable real-time applications in the field [11].

This study aims to develop and evaluate the classification model of palm kernel origin by combining thermal images and numerical agricultural data using MobileNet architecture. The stages carried out include collecting thermal image datasets and agricultural data from oil palm seeds, preprocessing data, extracting features using MobileNet, combining image features and agricultural numerical data, training classification models, and evaluating model performance using standard metrics such as accuracy, recall, precision, and F1-score.

2. METHOD

This research designs and develops a classification system for the origin of oil palm seeds by utilizing thermal images and agricultural data using MobileNet architecture. The development process is carried out systematically through structured phases, which are illustrated in Figure 1.

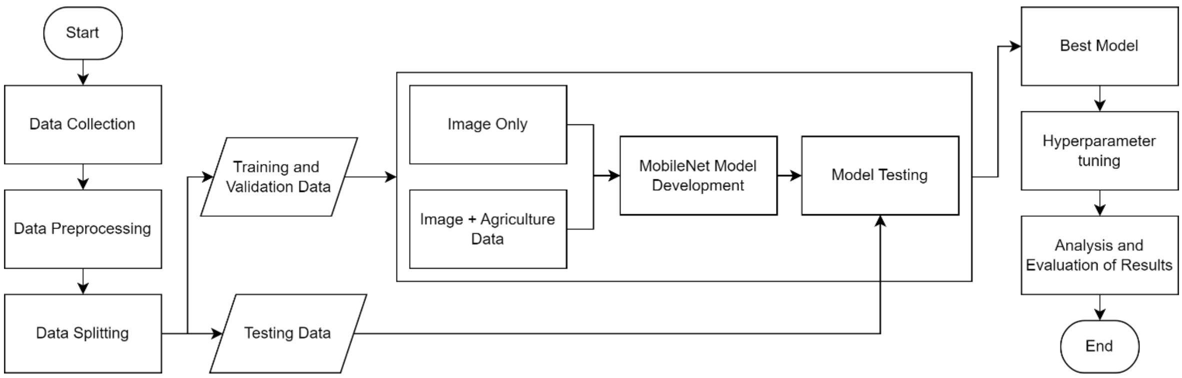

Figure 1. MobileNet-based palm kernel origin classification process diagram

2.1. Data Collection

The data used in this study consists of thermal images of oil palm seeds and agricultural data collected from various locations in oil palm plantations in Aceh Province, Indonesia. The thermal image dataset consists of a total of 7.257 photos of palm kernels representing 73 different seed origin classes. The agricultural data includes information on soil data, fruit analysis, and socio-economic data. All of this data is part of the research conducted by the Research Center for Rural Development and Sustainable

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Agriculture, Syiah Kuala University. Figure 2 shows examples of palm images taken using thermal cameras from various locations.

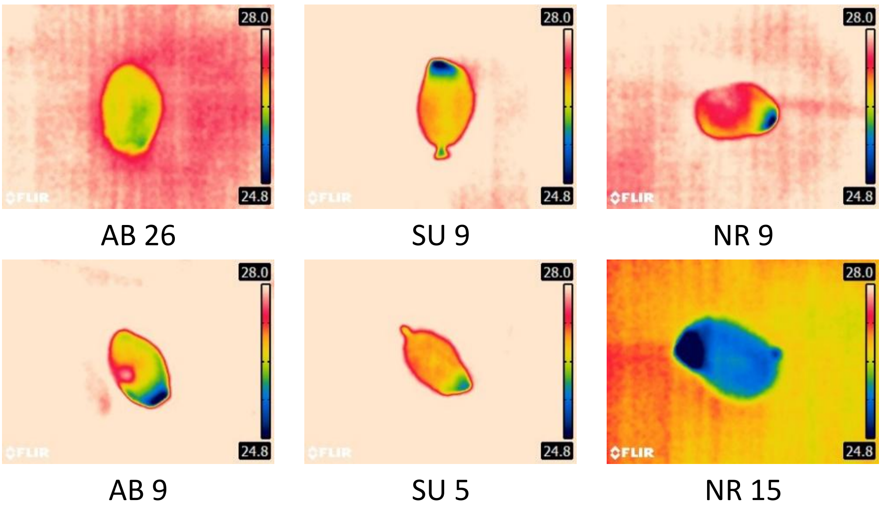

Figure 2. Thermal images of palm seeds from different regions

Further explanation of the figure is provided in Table 1.

Table 1. Example mapping of thermal image classes to regions and region numbers (partial data only)

Class Name	Region Name	Region Number
AB 26	Aceh Barat Daya	26
SU 9	30	9
3	50	9

2.2. Preprocessing

Data preprocessing is essential for enhancing the effectiveness of machine learning models. (2021) stated that preprocessing is the main basis for obtaining valid data analysis, especially when facing complex systems and frequent data quality problems [12]. Therefore, preprocessing is an important part of building an optimal and reliable analysis model. The main stages in preprocessing include handling missing values and duplicate data, data labeling, data transformation, data normalization, feature selection as well as systematic division of datasets to improve data quality while ensuring the accuracy of analysis results. These stages are further explained in sections 2.2.1 to 2.2.6.

2.2.1. Handling Missing Value and Duplicate Data

To handle missing values in the data, a SimpleImputer technique with an average-based filling strategy is used. This method replaces the missing values in each feature with the average value of the feature in question [13]. The use of this strategy was chosen due to its ease of implementation and its ability to maintain the stability of the data distribution, thus not adding significant bias to the model. In addition to handling missing values, duplicate data was also removed which could lead to inaccurate model training. This process aims to ensure that each data used for model training is unique and relevant to avoid potential bias caused by repetition of unwanted data.

2.2.2. Labeling Data

The data labeling process is carried out based on the origin of the oil palm seeds to distinguish each class that will be used in the classification stage. Each class is labeled with a categorical code such

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as AB1, AB2, AB3, NR1, NR2 and so on that represents a particular seed origin. To facilitate processing by machine learning models, these categorical labels are then encoded into numerical values using the Label Encoding technique.

Since the dataset used includes two types of data namely thermal images and agricultural data, both types of data are labeled with a uniformly structured format. This approach ensures that the imagery and agricultural data can be easily and consistently combined based on the same labels and enables effective data integration in the entire training and evaluation process of the classification model.

2.2.3. Data Transformation

Data transformation is done to ensure that the additional features of agricultural data remain consistent, especially for values involving numeric ranges or special symbols such as '<' and '>'. Values in numeric ranges (e.g. "8 - 16") were transformed into the middle value of the range. While values with the '<' symbol (e.g. "<8") are subtracted by one unit, and values with the '>' symbol (e.g. ">80") are added by one unit. This step aims to transform the data into a more uniform format, thus improving the quality and readability of the input for the classification model. The results of the data transformation are provided in Table 2.

Table 2. Result of data transformation

Target	Altitut (Original)	Altitut (Transformed)	Lereng (Original)	Lereng (Transformed)
SU1	<200	199	8 – 16	12
NR19	<125	124	<8	7
NR26	125 – 1000	562,5	8 – 16	12

This table shows an example of applying transformation rules to agricultural data such as "Altitut" and "Lereng". Although this table shows only a small portion of the processed data, all other columns undergo similar transformations.

2.2.4. Data Normalization

In this research, normalization is applied using the z-score normalization method applied to additional non-image features, namely agricultural data. This process is done by utilizing StandardScaler from the scikit-learn library which transforms each feature to have a distribution where the standard deviation is one and the mean is zero [14]. This normalization aims to eliminate scale imbalances between features and ensure that every feature makes an equal contribution in the classification model. The normalization procedure follows the standard statistical formula as shown in Equation (1).

$$z = \frac{(x - u)}{s} \tag{1}$$

Where, z is the normalized feature value. x is the original feature value. u is the feature mean. s is the feature standard deviation.

2.2.5. Feature Selection

Feature selection is performed using the variance-based selection method. This method aims to identify features that have significant variability in the dataset, making it possible to remove features with low variance that are likely to make no meaningful contribution to the classification model [15]. The variance of each feature is determined using a formula as shown in Equation (2).

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \tag{2}$$

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Where σ^2 is the variance, x_i is the i-th data value, μ is the average of all feature values, and N is the number of data in the feature. Features with low variance will be removed, while features with high variance will be retained for the classification process.

This approach was selected because to its ease of use and efficiency in reducing the dimensionality of the data, thereby improving the efficiency of the model without sacrificing essential information to support classification accuracy. However, features with high variance are not always relevant for classification. Some features may have high variance but most of the values are similar or do not show significant distribution patterns. Such features do not provide useful additional information to distinguish between classes, so they will be ignored in the feature selection process. The results of the variance of each data can be seen in Table 3.

Table 3. Agricultural data variance results

```
socioeconomic data variance results:
Harga TBS                        153737.802240
Umur                                146.811009
Lama Usahatani Kelapa Sawit          43.308343
Umur Tanaman (Tahun)                 35.137366
Produktivitas (Ton/ha/Thn)           33.142398
Produksi (Ton/Bulan)                 18.497039
Luas Lahan (Ha)                       8.766619
Jenis Dokumen Lahan                   2.479826
Pendidikan Terakhir                   1.413210
Varietas Bibit                        1.351562
Pemupukan                             1.205274
ISPO                                  0.795238
Saluran Pemasaran                     0.678136
Jenis sertifikat tanah                0.576024
Bibit bersertifikat                   0.545507
Asal Bibit                            0.445865
Kepemilikan STDB                      0.044432
dtype: float64
```

```
soil data variance results:
KB          134.597287
KTK          32.142353
P-av          5.489611
pH (H2O)      1.320075
C-org         0.668977
N-tot         0.003426
K-dd          0.003316
K2O           0.000494
dtype: float64
```

```
fruit data variance results:
SPEKT 399,3      8717.806868
SPEKT 545,9      6802.895886
SPEKT 401,2      6735.522002
SPEKT 547,8      6608.778838
SPEKT 543,9      6342.489474
                     ...
SPEKT 1583,6      211.445205
SPEKT 1581,6      211.438213
SPEKT 1579,7      211.210523
ALB                23.651742
DENSITAS            0.008999
Length: 1871, dtype: float64
```

After calculating the variance of each feature, the next step is to set a threshold to select the most relevant features. Features that have a higher variance than the predetermined threshold are considered more informative and are selected for use in model development. Socioeconomic data was selected with a threshold of 100, land data with a threshold of 5, and fruit data with a threshold of 6000. Based on the results of this selection, features that meet the criteria of high variance are selected for use in the classification model. The features selected for use in model development can be seen in Table 4

Table 4. Features selected above the threshold

Class Name	Selected Feature
Socioeconomic	'Umur', 'Harga TBS'
Soil	'P-av', 'KTK', 'KB'
Fruit	'SPEKT 399,3', 'SPEKT 401,2', 'SPEKT 543,9', 'SPEKT 545,9', 'SPEKT 547,8'

2.2.6. Split Data

At this stage, the dataset is divided into three main subsets: training data, validation data, and testing data. A total of 10% of the overall data is allocated for testing data to objectively evaluate the final performance of the model. The remaining 90% is used for the training and validation process of the model. Of this 90%, 20% is separated as validation data for tuning and monitoring during training, while the remaining 80% is used to train the model. This systematic division of data aims to ensure the model can learn well while avoiding overfitting and obtaining a valid evaluation [16].

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2.3. MobileNet

MobileNet is a convolutional neural network architecture developed with the main goal of producing lightweight models that still have competitive performance. This efficient design makes it highly suitable for implementation on devices with limited power and computing resources, such as mobile device-based applications or real-time systems [17].

The main advantage of MobileNet lies in the use of depthwise separable convolution, which is a convolution technique that breaks the standard convolution process into two stages. The first is depthwise convolution which applies one filter to each input channel separately. Second, pointwise convolution which combines the results of the previous stage with 1×1 convolution [18][19]. This approach drastically reduces the number of parameters and computational burden when compared to conventional convolution [20].

The model was further adapted to support the integration of visual and numerical data in a single classification architecture. MobileNet is used as the feature extractor for the thermal image after the top layer is removed and followed by global average pooling to reduce the output to a fixed dimensional vector. This feature vector is then combined with the numerical vector of agricultural data through the concatenation layer. The concatenation results are processed by two dense layers with ReLU activation followed by a dropout layer as regularization to prevent overfitting before entering the output layer with softmax activation function to generate class predictions. This structure is designed to allow the model to effectively learn complex inter-modality relationships. The full architecture of the model is shown in Figure 3.

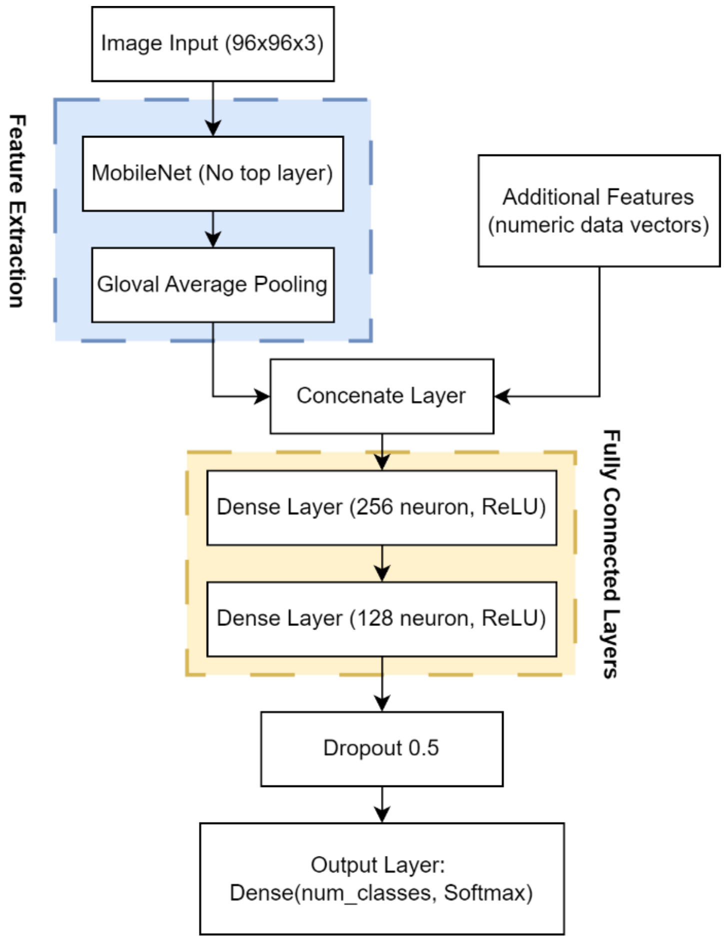

Figure 3. MobileNet-based classification architecture with additional features

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2.4. Hyperparameter Tuning

Hyperparameter tuning is necessary to achieve optimal model performance [21]. In the context of deep learning, choosing the right hyperparameter values can have a significant impact on the accuracy, convergence, and generalization ability of the model to data that has never been seen before. In this study, tuning is performed on several important parameters, namely batch size, learning rate, and optimizer, as shown in Table 5.

Table 5. Hyperparameter variations for model tuning

Parameter	Value
Batch size	16, 32, and 64
Learning rate	0.001 and 0.0001
Optimizer	Adam and SGD

This tuning process is applied specifically to the best model obtained from experiments using a combination of thermal images and agricultural data as input.

2.5. Confusion Matrix

Confusion matrix is a visual table used to assess the performance of a classification algorithm [22]. It provides important insights into evaluation metrics such as recall, accuracy, precision, and the overall effectiveness of the model in distinguishing between classes [23]. The way the confusion matrix works is by comparing the model's predicted results against the actual values of the test data, and then categorizing the results into four main categories: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). True Positive indicates the number of correct predictions for the positive class, while True Negative indicates the number of correct predictions for the negative class. False Positive describes incorrect predictions that classify negative cases as positive, while False Negative records positive cases that are incorrectly classified as negative. Analysis of these four components enables a thorough evaluation of the model's reliability, identifies emerging error patterns, and aids the optimization process to improve classification performance [24]. The confusion matrix representation can be seen in Table 6.

Table 6. Confusion matrix table

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Actual Value</td></tr>
<tr><td>Positive</td><td>Negative</td></tr>
<tr><td rowspan="2">Predicted Value</td><td>Positive</td><td>True Positive</td><td>False Positive</td></tr>
<tr><td>Negative</td><td>False Negative</td><td>True Negative</td></tr>
</table>

To assess the performance of the classification model, several evaluation metrics are calculated using the elements contained in the confusion matrix. The main metrics used include accuracy, precision, recall, and F1-score. The following is a brief explanation along with the calculation formula for each:

Accuracy calculates the proportion of accurate predictions among all tested data, as shown in Equation (3).

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{3}$$

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Precision indicates how accurate the model is in predicting positive classes, i.e. the proportion of correct positive predictions out of all positive predictions generated, as shown in Equation (4).

$$Precision = \frac{TP}{(TP + FP)} \tag{4}$$

Recall assesses the model's ability to detect all positive samples that actually exist in the dataset, as presented in Equation (5).

$$Recall = \frac{TP}{(TP + FN)} \tag{5}$$

F1-score is the harmonic mean of precision and recall, providing a measure of the balance between the two making it suitable for evaluation on unbalanced datasets, as shown in Equation (6).

$$F1 - Score = 2\frac{(Precision \times Recall)}{(Precision + Recall)} \tag{6}$$

3. RESULT

In this section, the results of training the palm kernel origin classification model using various MobileNet architectures and different combinations of data are discussed. The training process is carried out in stages, starting from the use of thermal images only, to integration with agricultural data to improve model performance. Furthermore, hyperparameter tuning is performed to obtain the best performing model.

3.1. MobileNet with thermal image only

In this experiment, the MobileNet V1 model is applied using only thermal images as input for palm kernel origin classification. Thermal images obtained from palm kernels are processed through MobileNet V1 which has been pre-trained using the ImageNet dataset. The model was built with the basic architecture of MobileNet V1 followed by multiple fully connected layers for final classification. With a batch size of 32 and a learning rate of 0.0001, the model was trained for 30 epochs. and using the Adam optimizer. The results of the experiment can be seen in Table 7.

Table 7. Training results with MobileNet V1 using thermal image only

Metric	Value
Training loss	0.0874
Validation loss	1.5887
Training accuracy	98.20%
Validation accuracy	64.80%
Test accuracy	63.22%

Based on these results, it can be seen that the model has high training accuracy (98.20%) and low train loss (0.0874), but the validation accuracy and test accuracy are relatively low at 64.80% and 63.22%, respectively. In addition, the high validation loss value (1.5887) indicates that the model is overfitting.

An illustration of the difference in training and validation performance is shown in the graph in Figure 4. The left graph shows a significant decrease in training loss to near zero, while the validation loss does not improve significantly after the 10th epoch. On the right side, the training accuracy increases consistently, but the validation accuracy stagnates at around 65%.

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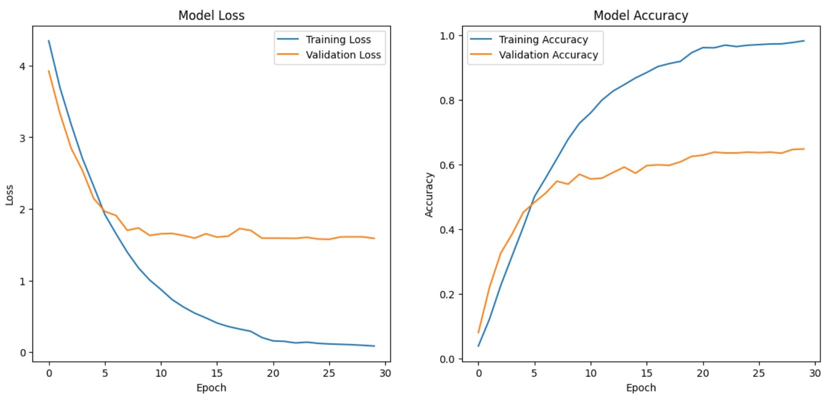

Figure 4. Loss and accuracy graph on MobileNet V1 model training on thermal image

These results show that the use of thermal imagery alone is not enough to produce a robust classification model. Therefore, future experiments will take an integrative approach by adding agricultural data as additional features to improve the prediction accuracy of the model.

3.2. MobileNet with thermal image only

To overcome the limitations of models that only use thermal imagery, this experiment integrates thermal images and agricultural data. The aim is to enrich the information received by the model so as to improve the generalization ability in palm kernel origin classification. This approach was tested using three variants of MobileNet, namely MobileNet V1, MobileNet V2, and MobileNet V3-Large.

In the architecture used, visual features from thermal images are extracted using the MobileNet model, while numerical data from soil, fruit, and socioeconomics are merged based on class labels into one feature vector per class. When the image is loaded, the corresponding numerical features are inserted automatically using the class name as a reference. Both inputs, image and agricultural data, are then scaled and divided into training, validation, and test data. The image extraction results and numerical features are combined using layer concatenation and then processed through multiple dense and dropout layers before classification.

Table 8. Training result of MobileNet model with combined thermal image and agricultural data

Metric	MobileNet V1	MobileNet V2	MobileNet V3 Large
Epoch	30	30	30
Batch size	32	32	32
Learning rate	0.0001	0.0001	0.0001
Optimizer	Adam	Adam	Adam
Training loss	0.0718	0.0989	0.0731
Validation loss	1.2699	1.2480	1.0572
Training accuracy	98.49%	97.84%	98.35%
Validation accuracy	71.00%	71.77%	74.06%
Test accuracy	69.70%	72.18%	75.62%

Based on the training results in Table 8, it can be seen that MobileNet V3-Large produces the best performance, with test accuracy reaching 75.62%, followed by MobileNet V2 (72.18%) and MobileNet V1 (69.70%). In addition, the V3-Large model also recorded the highest validation accuracy of 74.06% with the lowest validation loss, indicating better generalization ability compared to other variants.

Figure 5 shows the graphs of training loss and validation loss (left) and training accuracy and validation accuracy (right) during the training process for the MobileNet V3-Large model. From the graphs, it can be seen that the model is able to maintain a stable gap between the training and validation

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data, not too sharp as in previous experiments. Although there are still indications of mild overfitting, the model managed to reach a more balanced convergence point.

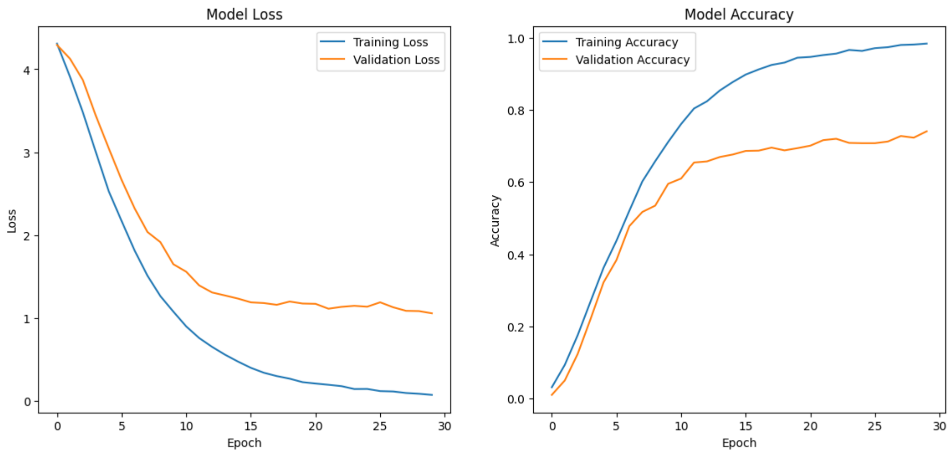

Figure 5. Loss and accuracy graph of MobileNet V3-Large model training with thermal image and agricultural data

Overall, the integration of agricultural data into the MobileNet architecture was shown to make a positive contribution towards improving classification accuracy. This suggests that non-visual features can provide important additional context in pattern recognition that cannot be captured from thermal images only.

3.3. Best Model and Hyperparameter Tuning

After selecting the best architecture, MobileNet V3-Large with combined input of thermal images and agricultural data, a hyperparameter tuning process was performed to optimize the model performance. This process involves exploring the combination of three main hyperparameters, namely batch size, learning rate, and optimizer. A total of 12 experimental combinations were run to determine the impact of each configuration on the model training and evaluation results. The results of the various parameter combinations are presented in Table 9.

Table 9. Hyperparameter tuning results on MobileNet V3-Large

Bacth size	Learning Rate	Optimizer	Epoch	Train Loss	Val Loss	Train Accuracy	Val Accuracy	Test Accuracy
16	0.001	Adam	20	0.0433	0.0770	98.77%	97.25%	99.04%
16	0.001	SGD	70	0.0272	0.3235	99.44%	91.66%	94.90%
16	0.0001	Adam	30	0.0612	0.7799	98.64%	80.95%	81.54%
16	0.0001	SGD	100	0.2786	0.6522	92.94%	80.80%	85.26%
32	0.001	Adam	20	0.0496	0.1813	98.81%	96.40%	95.32%
32	0.001	SGD	70	0.0350	0.5709	99.25%	84.47%	84.57%
32	0.0001	Adam	30	0.0751	1.0425	98.43%	73.30%	74.52%
32	0.0001	SGD	100	0.8064	1.2724	78.91%	66.72%	65.84%
64	0.001	Adam	20	0.0351	0.5385	98.99%	87.78%	89.94%
64	0.001	SGD	70	0.0515	1.0853	99.20%	72.07%	72.31%
64	0.0001	Adam	30	0.0903	1.5328	98.20%	61.13%	64.88%
64	0.0001	SGD	100	1.9339	2.3165	51.49%	45.60%	44.63%

Of all the combinations, the configuration with batch size 16, learning rate 0.001, and optimizer Adam showed the best performance, with the highest test accuracy of 99.04%, validation accuracy of

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97.25%, and very low train loss and validation loss (0.0433 and 0.0770). This shows that the model is able to learn efficiently and still has good generalization ability on both validation and test data.

Figure 6 displays the loss and accuracy graphs of the best hyperparameter combination. It can be seen that the model quickly reaches convergence in only 20 epochs. Validation accuracy continues to increase and almost matches the training accuracy, indicating stable training and minimal overfitting.

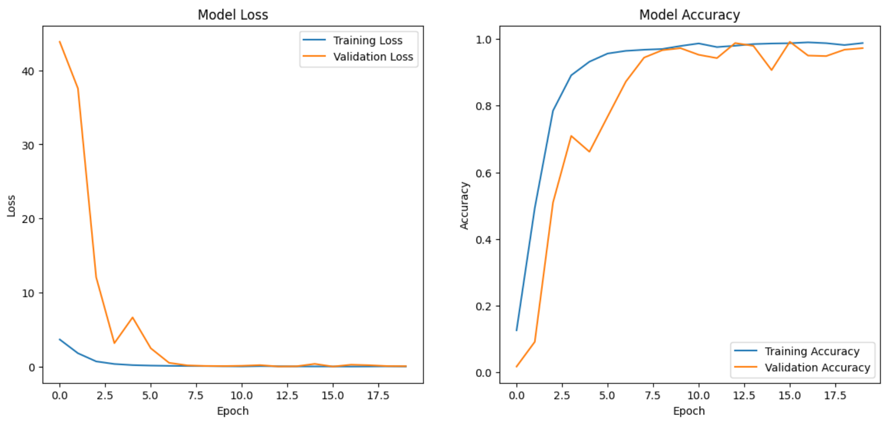

Figure 6. Loss and Accuracy graph for the best hyperparameter combination (Batch size 16, LR 0.001, Optimizer Adam)

In this experiment, the number of epochs was adjusted between Adam and SGD. Adam is known to have an adaptive mechanism to the learning rate during training, making it faster to reach convergence. Meanwhile, the SGD optimizer requires more epochs to achieve optimal results due to its more explicit nature in parameter updates. This difference is reflected in the configuration, where the combination with SGD is executed up to 70-100 epochs to obtain maximum results.

These tuning results prove the importance of hyperparameter selection in deep learning, and show that a combination of the right architecture and careful tuning can significantly improve model accuracy.

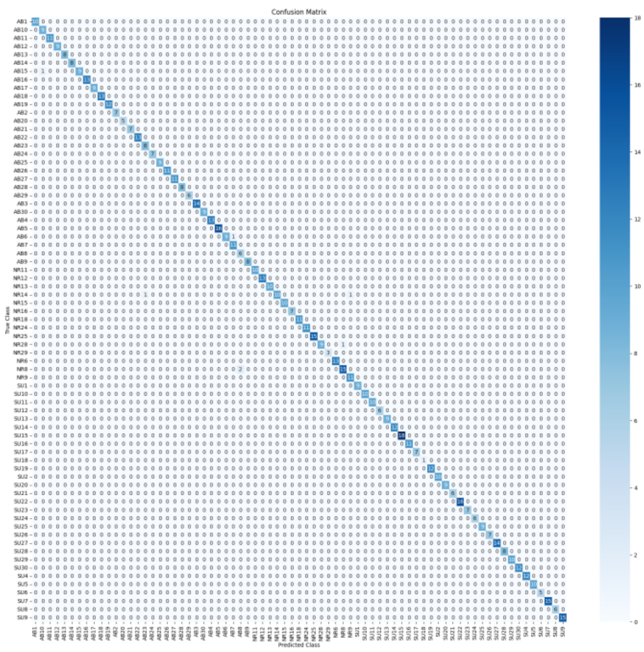

Figure 7. Best model confusion matrix MobileNet V3-Large

The classification results of the MobileNet V3 Large model are shown through the confusion matrix in Figure 7. In general, the model is able to classify most of the 73 classes very well. Each class

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has a predominant distribution of predictions on the main diagonal, indicating high accuracy and minimal misclassification between classes. Some classes even achieve perfect predictions with no misclassification (zero values in all columns other than the diagonal), reflecting the strength of the model's representation of these classes.

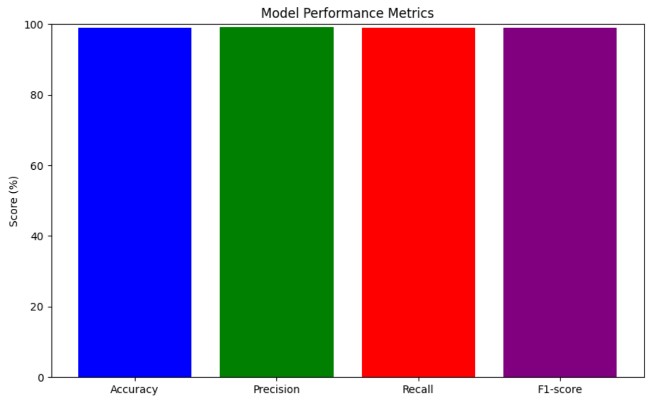

Figure 8. Best model performance metrics

The model performance metrics shown in Figure 8 demonstrate the excellent evaluation performance of the classification model against the test data. This result reflects the high generalization rate of the model with 99.04% accuracy, other important aspects such as 99.15% precision, 99.04% recall, and 99.04% F1-score. The almost identical values of recall and precision indicate that the model is able to maintain a balance between correctly recognizing classes and avoiding erroneous predictions, even in a multi-class scenario with 73 labels. The stability of these scores also indicates that there is no significant overfitting of the training data, and the model is able to handle complex data distributions consistently. In other words, this high performance is not just a result of optimization for accuracy, but is a result of the effective integration of visual and numerical features in capturing relevant patterns from the data.

4. DISCUSSIONS

This research proposes an approach to classifying the origin of oil palm seeds using a combination of thermal images and agricultural data by utilizing MobileNet architecture. The results obtained show that the integration of thermal image data and agricultural features is able to improve the accuracy of the classification model compared to the use of thermal images alone. This finding reinforces the importance of combining visual and non-visual information in building reliable machine learning models in precision agriculture.

The MobileNet model trained only with thermal images shows good performance, this is in line with the results of research from Zolfagharnassab et al. (2022) who showed that the temperature difference between the fruit and the surrounding environment from thermal images can be used effectively to classify the ripeness level of palm fruits [7]. Furthermore, this result is also consistent with the findings of Puttinaovarat et al. (2024) who showed that the combination of image data with spatial information and farm attributes can improve the accuracy of palm fruit maturity classification in the field [25]. In their study, the use of the MobileNet model on mobile devices resulted in high accuracy for two-class classification (ripe and immature) demonstrating the effectiveness of an integrated image-based approach.

The choice of MobileNet in this research is appropriate given the need for computational efficiency for deployment in edge or field devices. Although MobileNet is architecturally lighter than

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the more complex convolutional model, the results obtained show that it is quite responsive to the integration of different types of data, especially after the addition of non-visual data.

Hyperparameter tuning experiments show that longer epoch configurations tend to be used when the model is trained using the SGD optimizer which requires more time for convergence compared to Adam. In addition, variations in learning rate, batch size, and optimizer show significant influence on the accuracy of the final model. This confirms the importance of choosing the right hyperparameters to optimize model performance.

This research contributes to the field of computer science, particularly to computer vision and its application in digital agriculture by demonstrating the effectiveness of integrating different data types such as thermal images and structured agricultural features into a lightweight artificial neural network architecture. The proposed integration method not only improves classification accuracy in multi-class scenarios, but also highlights the potential of applying efficient classification models such as MobileNet on edge devices for real-time agricultural monitoring. This integration approach offers a scalable and practical solution that can be adopted in precision farming systems, thus paving the way for smarter and data-driven decision-making in seed grading.

5. CONCLUSION

This research successfully developed an oil palm seed origin classification model by combining thermal images and agricultural data using MobileNet architecture. The results obtained show that the integration of visual (thermal images) and non-visual information (agricultural data) significantly improves the accuracy of the model when compared to the use of thermal images alone. In the experiments conducted, the MobileNet V3 Large model gave the best results after hyperparameter tuning with test accuracy reaching 99.04%, as well as training accuracy 98.77% and validation accuracy 97.25%. The dataset used in this study consists of 7,257 images with 73 classes of oil palm seed origin.

Although the MobileNet V3 model provides the best performance among other architectures, this study also shows the importance of selecting the right hyperparameters, such as learning rate, batch size, and optimizer to optimize the model performance. These factors have a significant influence on the final results.

In the future, this research can be extended with more extensive and representative data collection and the application of more complex models for further applications. The main focus of future research should be on developing a real-time classification system that can operate in the field, especially using mobile devices, to enable wider implementation of this technology in the palm oil industry and precision agriculture.

CONFLICT OF INTEREST

The authors confirm that no conflicts of interest exist among the authors or in relation to the research object presented in this study.

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REFERENCES

[1] R. Santosa, H. Haryadi, and D. Artis, “Analisis faktor-faktor yang mempengaruhi ekspor minyak kelapa sawit Indonesia ke Uni Eropa,” *e-Journal Perdagangan Industri dan Moneter*, vol. 10, no. 1, pp. 63–70, Mar. 2022, doi: 10.22437/pim.v10i1.14212.
[2] “BADAN PUSAT STATISTIK BPS-STATISTICS INDONESIA,” 2024.

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https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.1.4879

[3] H. Tandra, A. I. Suroso, Y. Syaukat, and M. Najib, "The Determinants of Competitiveness in Global Palm Oil Trade," *Economies*, vol. 10, no. 6, p. 132, Jun. 2022, doi: 10.3390/economies10060132.
[4] D. L. Corwin, "Climate change impacts on soil salinity in agricultural areas," *Eur J Soil Sci*, vol. 72, no. 2, pp. 842–862, Mar. 2021, doi: 10.1111/ejss.13010.
[5] H. Singh, B. K. Northup, C. W. Rice, and P. V. V. Prasad, "Biochar applications influence soil physical and chemical properties, microbial diversity, and crop productivity: a meta-analysis," *Biochar*, vol. 4, no. 1, p. 8, Dec. 2022, doi: 10.1007/s42773-022-00138-1.
[6] M. A. Farooq, W. Shariff, D. O'callaghan, A. Merla, and P. Corcoran, "On the Role of Thermal Imaging in Automotive Applications: A Critical Review," *IEEE Access*, vol. 11, pp. 25152–25173, 2023, doi: 10.1109/ACCESS.2023.3255110.
[7] S. Zolfagharnassab, A. R. B. M. Shariff, R. Ehsani, H. Z. Jaafar, and I. Bin Aris, "Classification of Oil Palm Fresh Fruit Bunches Based on Their Maturity Using Thermal Imaging Technique," *Agriculture*, vol. 12, no. 11, p. 1779, Oct. 2022, doi: 10.3390/agriculture12111779.
[8] E. Elfatimi, R. Eryigit, and L. Elfatimi, "Beans Leaf Diseases Classification Using MobileNet Models," *IEEE Access*, vol. 10, pp. 9471–9482, 2022, doi: 10.1109/ACCESS.2022.3142817.
[9] R. R. Danda, "Innovations in Agricultural Machinery: Assessing the Impact of Advanced Technologies on Farm Efficiency," *Journal of Artificial Intelligence and Big Data*, vol. 2, no. 1, pp. 64–83, May 2022, doi: 10.31586/jaibd.2022.1156.
[10] S. A. Bhat and N.-F. Huang, "Big Data and AI Revolution in Precision Agriculture: Survey and Challenges," *IEEE Access*, vol. 9, pp. 110209–110222, 2021, doi: 10.1109/ACCESS.2021.3102227.
[11] M. Francis, K. S. M. Anbananthen, D. Chelliah, S. Kannan, S. Subbiah, and J. Krishnan, "Smart Farm-Care using a Deep Learning Model on Mobile Phones," *Emerging Science Journal*, vol. 7, no. 2, pp. 480–497, Feb. 2023, doi: 10.28991/ESJ-2023-07-02-013.
[12] C. Fan, M. Chen, X. Wang, J. Wang, and B. Huang, "A Review on Data Preprocessing Techniques Toward Efficient and Reliable Knowledge Discovery From Building Operational Data," *Front Energy Res*, vol. 9, Mar. 2021, doi: 10.3389/fenrg.2021.652801.
[13] J. Li *et al.*, "Comparison of the effects of imputation methods for missing data in predictive modelling of cohort study datasets," *BMC Med Res Methodol*, vol. 24, no. 1, p. 41, Feb. 2024, doi: 10.1186/s12874-024-02173-x.
[14] C. Edlund *et al.*, "LIVECell—A large-scale dataset for label-free live cell segmentation," *Nat Methods*, vol. 18, no. 9, pp. 1038–1045, Sep. 2021, doi: 10.1038/s41592-021-01249-6.
[15] A. Bommert, T. Welchowski, M. Schmid, and J. Rahnenführer, "Benchmark of filter methods for feature selection in high-dimensional gene expression survival data," *Brief Bioinform*, vol. 23, no. 1, Jan. 2022, doi: 10.1093/bib/bbab354.
[16] I. Muraina, "IDEAL DATASET SPLITTING RATIOS IN MACHINE LEARNING ALGORITHMS: GENERAL CONCERNS FOR DATA SCIENTISTS AND DATA ANALYSTS," Jun. 2022.
[17] Y. Lin, Y. Zhang, and X. Yang, "A Low Memory Requirement MobileNets Accelerator Based on FPGA for Auxiliary Medical Tasks," *Bioengineering*, vol. 10, no. 1, p. 28, Dec. 2022, doi: 10.3390/bioengineering10010028.
[18] P. Zhang, E. Lo, and B. Lu, "High Performance Depthwise and Pointwise Convolutions on Mobile Devices," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, no. 04, pp. 6795–6802, Apr. 2020, doi: 10.1609/aaai.v34i04.6159.
[19] W. Wang, Y. Hu, T. Zou, H. Liu, J. Wang, and X. Wang, "A New Image Classification Approach via Improved MobileNet Models with Local Receptive Field Expansion in Shallow Layers," *Comput Intell Neurosci*, vol. 2020, pp. 1–10, Aug. 2020, doi: 10.1155/2020/8817849.
[20] J. Liu, M. Li, Y. Luo, S. Yang, W. Li, and Y. Bi, "Alzheimer's disease detection using depthwise separable convolutional neural networks," *Comput Methods Programs Biomed*, vol. 203, p. 106032, May 2021, doi: 10.1016/j.cmpb.2021.106032.
[21] H. Jin, "Hyperparameter Importance for Machine Learning Algorithms," Jan. 2022.
[22] S. Sathyanarayanan, "Confusion Matrix-Based Performance Evaluation Metrics," *African Journal of Biomedical Research*, pp. 4023–4031, Nov. 2024, doi: 10.53555/AJBR.v27i4S.4345.

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https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.1.4879

[23] C. S. Hong and T. G. Oh, "TPR-TNR plot for confusion matrix," *Commun Stat Appl Methods*, vol. 28, no. 2, pp. 161–169, Mar. 2021, doi: 10.29220/CSAM.2021.28.2.161.
[24] M. Heydarian, T. E. Doyle, and R. Samavi, "MLCM: Multi-Label Confusion Matrix," *IEEE Access*, vol. 10, pp. 19083–19095, 2022, doi: 10.1109/ACCESS.2022.3151048.
[25] S. Puttinaovarat, S. Chai-Arayalert, and W. Saetang, "Oil Palm Bunch Ripeness Classification and Plantation Verification Platform: Leveraging Deep Learning and Geospatial Analysis and Visualization," *ISPRS Int J Geoinf*, vol. 13, no. 5, p. 158, May 2024, doi: 10.3390/ijgi13050158.