Classification of forest and land fire severity levels using convolutional neural network

Assad Hidayat[1*], *Imas Sukaesih* Sitanggang [1], and *Lailan* Syaufina[2]

[1]Department of Computer Science, FMIPA IPB, Bogor, Indonesia
[2]Department of Silviculture, Faculty of Forestry and Environment IPB, Bogor, Indonesia

Abstract. Forest and land fires have significant negative impacts on the environment, economy, and public health. These fires cause damage to forest ecosystems, resulting in loss of biodiversity, air quality degradation, and climate change. Assessment of areas post-forest and land fires is crucial for measuring the severity level and planning appropriate rehabilitation measures. This research focus to classify the severity levels of forest and land fires based on photo data obtained from field locations in four villages in Jambi Province. The dataset will be trained into a model using Convolutional Neural Network (CNN) with MobileNetV2 architecture. Based on the evaluation results of training the MobileNetV2 model with two image sizes, (224, 224) and (112, 112), using 50 epochs, it is shown that the highest accuracy was obtained from the model with both image sizes, with an accuracy value of 77.7% and the lowest loss value of 0.618. The use of MobileNetV2 architecture model yielded satisfactory results. MobileNetV2 was considered superior in analyzing the classification model performance on the data used, but there is a need for additional field photo data to improve model training.

1 Introduction

Forest and land fires (karhutla) are phenomena that threaten human safety, infrastructure, and biodiversity. Fires also have significant economic and social consequences at regional and local levels [1]. There are many factors causing karhutla, impacting several countries with extensive forests, such as Indonesia. The forest area in Indonesia continues to shrink year by year. Cumulatively, in 2023, the Ministry of Environment and Forestry (KLHK) documented forest fires occurring in Indonesian territory covering an area of 994,313.18 hectares [2]. Karhutla usually occurs in areas with two soil characteristics: peat soil and mineral soil. The difference in the properties of these two soils is that mineral soil has a low organic matter content, while peat soil has a relatively high organic matter content. It is necessary to understand the impact of karhutla on both types of soil to serve as a basis for early assessment of post-fire areas in Indonesia [3]. The handling of karhutla in post-fire areas needs to be carried out and documented, as this data will serve as a basis for measuring the severity of karhutla.

* Corresponding author : assadhidayat@apps.ipb.ac.id

The severity of karhutla can be described as a term reflecting the impact of fire on flora, fauna, ecosystems, rivers, atmosphere, and humans [4]. The method previously used is observation-based, involving direct measurements using an aggregate scoring method based on two criteria: vegetation condition (70%) and soil condition (30%) [5]. Direct field measurement of karhutla severity requires a long time and considerable expense. The best solution is to perform remote measurements utilizing tools or technologies capable of processing image data [6]. The image data obtained can be processed using certain techniques to analyze the severity of wildfires, one of which is by utilizing Convolutional Neural Network (CNN) deep learning. CNN have the capability to automatically extract intricate features from images, thus bypassing the intricacies and limitations associated with manual feature extraction. In contrast, conventional image processing techniques rely on manual feature extraction algorithms grounded in prior knowledge. However, given the distinct characteristics of karhutla images, these manually devised feature extraction algorithms frequently prove inadequate, underscoring the necessity of employing CNN [7].

Research related to image data processing of karhutla using CNN has been conducted by Zheng et al. [8], yielding excellent performance with an average accuracy of 95.7%. Additionally, Khan et al. [9] conducted a study on forest fire classification using the MobileNetV2 CNN architecture in smart cities, achieving an accuracy of 98.42%. Furthermore, research by Gürsoy et al. [10] in the Mediterranean region using CNN showed that the CNN model performed excellently in assessing forest fires with an accuracy of 85.8%. These findings can help government organizations and decision makers in preventing the severity of wildfires in the future.

Based on the above exposition, supported by previous research, this study aims to implement a classification model to determine the severity level of wildfires using the CNN architecture MobileNetV2 on image data obtained from the study area. Furthermore, it seeks to find the optimal performance of MobileNetV2 in classifying image data of wildfires severity based on the accuracy metric generated.

2 Methodology

This research is conducted through several stages such as data collection, data preprocessing, data classification using the CNN algorithm MobileNetV2 architecture using Python in Jupyter Notebook, methodology of this research showed in Figure 1.

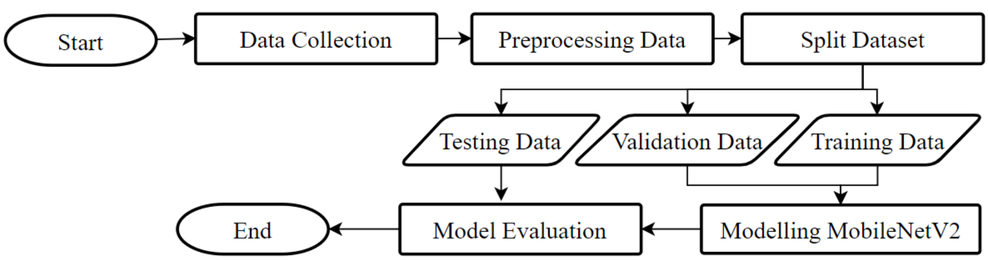

Fig. 1. Methodology

2.1 Data Collection

The dataset for this research was obtained from direct field photo capture. The data consists of photos taken after handling karhutla in four villages in Jambi Province, namely Pematang Rahim, Pematang Lumut, Pelanyangan, and Tenam. The dataset used comprises 90 photos after the karhutla handling. The description of the data to be processed in this study based on severity class can be seen in Figure 2.

 https://doi.org/10.1051/bioconf/202412301030

(a) (b) (c)

Fig. 2. Dataset images of post-fire conditions: severe (a), moderate (b) and light (c)

2.2 Data Preprocessing

Preprocessing is a step aimed at manipulating the dataset to conform to the predetermined architecture, thus making it suitable as input. In this study, the data preprocessing stage to determine the severity level of karhutla is conducted using a deep learning approach employing the MobileNetV2 architecture as the basic model and incorporating supplementary layers for classification output. Subsequently, the preprocessing steps for image data include resizing images to (224, 224) and (112, 112), rescaling to 1./255, setting rotation range to 40, enabling horizontal flip, and using nearest as the fill mode.

2.3 Split Dataset

The data separation process in MobileNetV2 or generally in the context of deep learning involves steps aimed at dividing the dataset into training subsets, validation subsets and test subsets. In this study, the data division is 70% for training data and 30% for validation data. Data is also separated based on the severity level of karhutla, namely mild, moderate, severe, where the classification of karhutla severity levels depends on the conditions and characteristics of the soil in the burned area. The severity levels of fire in this study are referenced from the research by Saharjo et al [11].

2.4 Convolutional Neural Network

Convolutional Neural Network (CNN) modeling is a variety of Multilayer Perceptron (MLP), specifically to process 2D data. Conceptually, CNNs are not significantly different from regular neural networks. CNNs are one of the common types of neural networks applied to image data, typically used for object identification and recognition in images [12]. The architecture CNN and typical blocks can be seen in Figure 3.

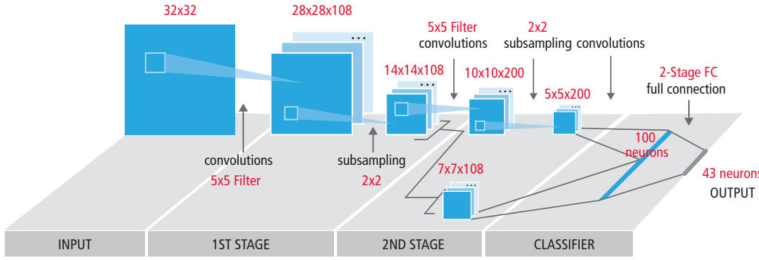

Fig. 3. Typical blok on CNN [13]

2.4.1 Convolution Layer

The meaning that layer is a crucial component for the architecture of CNN. In this step, convolution operates on the output of the previous process. This layer is the core element that fundamentally exists in CNN architecture [14]. The operation of the convolution process by Ker et al. is depicted in the equation 1.

$$s(t) = (x * t)\ (t) = \sum_{a=-\infty}^{\infty} x(a) * w(\ t - a\ ) \tag{1}$$

2.4.2 Pooling Layer

This layer is the application of pooling operators to gather information in small regions of input feature channels and then sample the results. The focus of the pooling layer is to gradually reduce the dimensions of the representation, thereby reducing the number of parameters and the overall computational complexity of the algorithm [15].

2.4.3 Fully Connected Layer (FCL)

The stage in the FCL is a process where each active neuron in the previous layer is connected to every neuron in the subsequent layer, resembling the structure of a typical neural network. The purpose of FCL is to transform the data dimensions for linear classification. FCL consists of several components, including loss function, activation functions, hidden layers and output layers [16].

2.5 MobileNetV2

MobileNetV2 is utilized for image classification and focuses on model portability. This model employs Depthwise Separable Convolutions (DSC) and can be considered state-of-the-art, with several layers following behind for specific classification tasks [17]. The Inverted Block is expanded by increasing the number of features. Another type of block used in MobileNetV2 is the Residual Inverted Block (ResBlock). MobileNetV2 is renowned for its superior performance in classification model analysis. Lightweight, meaning it requires less storage space and fewer computations [18].

3 Results

The training model used to classify the severity of wildfires in this research is MobileNetV2, which includes a CNN architecture, utilizing image data obtained from the study area. The initial step involves data splitting through training sets and validation sets. The division of training data and validation data is 70% of the total data for training data, and then 30% for validation data. Each directory in the training and validation data groups them based on their classes, namely mild, moderate, and severe. After data splitting, the data undergo normalization and resizing into two experiments, namely (224,224) and (112,112).

The normalization process of the data aims to create a set of variables with uniformly scaled values, neither too high nor too low, which can enhance the model learning performance. All pixels in the image are multiplied by 1./255. The model is trained with

dropout rate of 0.5, 50 epochs, a batch size of 32, using activation function of ReLU, Adam optimizer, loss function categorical crossentropy, accuracy metric, and softmax activation function is used in the last layer. The result of training the model with 50 epochs on an image size of (224, 224) yields an accuracy of 77.7% and loss value of 0.662 depicted in Figure 4.

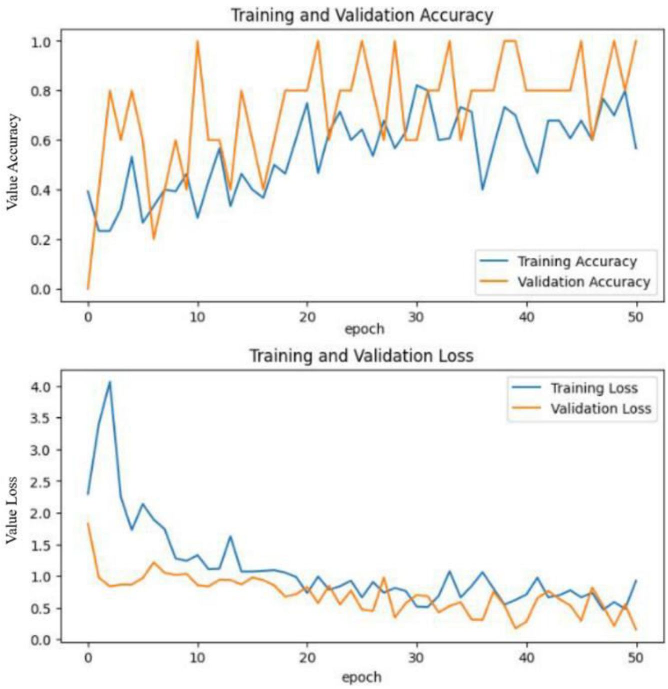

Fig. 4. Accuracy and loss diagram for image size (224, 224) on training and validation

The result of training the model with 50 epochs on an image size of (112, 112) yields an accuracy of 70.23% and a loss value of 0.618. The graph appears as shown in Figure 5.

Fig. 5. Accuracy and loss diagram for image size (112, 112) on training and validation

Here are the accuracy metrics for the MobileNetV2 model trained using image sizes (224, 224) and (112, 112), both with 50 epochs, and with a training-validation data split of 70% and 30% respectively from the total data. The following results show that image size affects the level of accuracy, can be seen in Table 1.

Table 1. Accuracy and loss based on image size and epoch.

Image size	Epoch	Accuracy	Loss Value
224, 224	50	77,7%	0,662
112, 112	50	70,23%	0,618

4 Discussion

The results showed that the model with image size (224, 224) achieved the highest accuracy of 77.7%, compared to image size (112, 112) which achieved an accuracy of 70.23%. This difference indicates that higher image resolution provides better detail and allows the model to capture more complex features in the image. This result is consistent with the findings by Khan et al. [9], which showed that CNN models with higher image resolution tend to provide more accurate classification results. This is because larger image sizes provide more information that can be used by the model to recognize subtle patterns and specific features in the image. Research by Gürsoy et al. [10] also supports this finding, where CNN models show improved performance with the use of higher image resolution in assessing forest fires. However, the difference in results between this study and that of Zheng et al. [8], which achieved 95.7% accuracy, suggests possible differences in data quality, preprocessing techniques, or model parameters used. Zheng et al. used a dataset that may differ in terms of image variability and image capture conditions. This study uses

photo data from four villages in Jambi Province, which may have variations in environmental and lighting conditions that affect image quality and model results.

The model shows the lowest loss value of 0.618 at image size (112, 112), compared to image size (224, 224) which has a loss value of 0.662. While larger image sizes improve accuracy, the more computationally intensive process can increase the loss value, especially if the model is over-fitted to the training data. This suggests the need for a balance between image size and model complexity to avoid overfitting. Limitations of this study include the limited amount of data and variations in image conditions that may affect the accuracy of the model. Further research is recommended to collect more data from different locations and fire conditions, and explore data augmentation techniques to improve model performance.

5 Conclusion

Based on the above exposition, this study has successfully built a classification model to identify the severeness level of wildfires using the CNN architecture MobileNetV2, with two experiments involving image sizes (224, 224) and (112, 112), each trained for 50 epochs. The algorithm demonstrates that the best performance achieved using the accuracy metric is 77.7%, with the lowest loss value being 0.618. The utilization of the MobileNetV2 architecture model in classifying the severity level of forest and land fires on the utilized data yields quite satisfactory results.

For future improvements, it is recommended to add more photos of post-handling forest and land fire areas, thereby deepening the model training process. If the training process yields very good model accuracy, then the model can be deployed to a mobile platform, as MobileNetV2 is considered superior in performance analysis for classification models on mobile platforms. This could lead innovation in controlling forest and land fire in Indonesia.

References

1. A.L.R. Westerling, Increasing western US forest wildfire activity: Sensitivity to changes in the timing of spring, Philosophical Transactions of the Royal Society B: Biological Sciences. **371**, 1696 (2016)
2. The Ministry of Environment and Forestry of the Republic of Indonesia. [internet] https://ppid.menlhk.go.id/berita/siaran-pers/7579/kinerja-pengendalian-kebakaran-hutan-dan-lahan-tahun-2023. [27 Februari 2024] (2023)
3. A.R. Kusuma AR, F.M. Shodiq, M.F. Hazim, D.P. Laksono, Hasil Studi Pola Kebakaran Lahan Gambut melalui Citra Satelit Sentinel-2 dengan Pengimplementasian Machine Learning Metode Random Forest: Kajian Literatur. JGISE. **4**, 2 (2021)
4. L. Syaufina, Metode Penilaian Areal Pasca Kebakaran Hutan. IPB Press: Bogor, Indonesia (2017)
5. L. Syaufina, A.A. Hamzah, Changes of tree species diversity in peatland impacted by moderate fire severity at Teluk Meranti, Pelalawan, Riau Province, Indonesia. Biodiversitas. **22**, 5 (2021)
6. M. Arrafi, L. Somantri, R. Ridwana, Pemetaan Tingkat Keparahan Kebakaran Hutan dan Lahan Menggunakan Algoritma Normalized Burn Ratio (NBR) Pada Citra Landsat 8 di Kabupaten Muaro Jambi. Jurnal Geosains dan Remote Sensing. **3**, 1 (2022)
7. Y.Q. Guo, G. Chen, Y.N. Wang, X.M. Zha, Z.D. Xu, Wildfire Identification Based on an Improved Two-Channel Convolutional Neural Network. Forests. **13**, 1302 (2022)

8. X. Zheng, F. Chen, L. Lou, P. Cheng, Y. Huang, Real-Time Detection of Full-Scale Forest Fire Smoke Based on Deep Convolution Neural Network. Remote Sens. **14**, 536 (2022)
9. S. Khan, A. Khan, Firenet: Deep learning based forest fire classification and detection in smart cities. Symmetry. **14**, 10 (2022)
10. M.I. Gürsoy, O. Orhan, S. Tekin, Creation of wildfire susceptibility maps in the Mediterranean Region (Turkey) using convolutional neural networks and multilayer perceptron techniques. Forest Ecology and Management. **538,** 121006 (2023)
11. B.H. Saharjo, L. Syaufina, A.D Nurhayati, E.I. Putra, R.D. Waldi, Wardana, Pengendalian Kebakaran Hutan Dan Lahan Di Wilayah Komunitas Terdampak Asap (IPB Press: Bogor, Indonesia, 2018)
12. R.P. Sadewa, B. Irawan, C. Setianingsih, Fire Detection Using Image Processing Techniques with Convolutional Neural Networks. ISRITI (2019)
13. S. Hijazi, R. Kumar, C. Rowen, Using Convolutional Neural Networks for Image Recognition. IP Group. Cadence (2015)
14. J. Ker, L. Wang, J. Rao,T. Lim, Deep Learning Applications in Medical Image Analysis, IEEE Access. **6** (2018)
15. K. O'Shea, R. Nash, An introduction to convolutional neural networks. arXiv preprint arXiv:1511.08458 (2015)
16. A. Santoso, G. Ariyanto, Implementasi Deep Learning Berbasis Keras Untuk Pengenalan Wajah. Emit. J. Tek. Elektro. **18**, 01 (2018)
17. K. Dong, Zhou, C. Zhou, Y. Ruan, Y. Li, MobileNetV2 Model for Image Classification. ITCA (2020)
18. J.H. Roh, S.H Min, M.S. Kong, Analysis of Fire Prediction Performance of Image Classification Models based on Convolutional Neural Network. Fire Science and Engineering. **36**, 6 (2022)