



PERFORMANCE EVALUATION OF DEEP LEARNING-BASED SEGMENTATION MODELS FOR SMALL BURNED AREA DETECTION IN LANDSAT-8 IMAGES

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ABSTRACT

Accurate and timely burned area mapping is crucial for post-fire management, planning, and mitigation strategies. Traditional approaches for burned area detection are often time-consuming and challenging, highlighting the need for more efficient and automated methods. This study investigates the performance of several deep learning-based segmentation models, including DeepLab, ResNet50, ResNet101, ResNet152, and Attention U-Net, for burned area detection using Landsat-8 satellite imagery in Indonesia. The models were trained and evaluated on a publicly available burned area dataset derived from previous research. Experimental results indicate that all models exhibit limited segmentation performance on the dataset. Among the evaluated models, ResNet50 achieved the best results with a mean Intersection over Union (IoU) of 0.1939 and a Dice coefficient of 0.2645. Deeper architectures such as ResNet101 and ResNet152 did not yield performance improvements, likely due to dataset limitations and model complexity. These findings highlight the challenges of burned area segmentation in satellite imagery and suggest the need for improved model design, data preprocessing, and feature representation to enhance segmentation accuracy.



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I. INTRODUCTION

Forest fires are one of the major environmental disasters that significantly impact ecosystems [1], air quality, and carbon emissions [2], [3]. In countries such as Indonesia, wildland fires occur frequently, especially during the dry season, causing large-scale deforestation and ecological degradation [4]. Therefore, accurate and timely mapping of burned areas is essential for post-fire management, environmental monitoring, and decision-making processes [5], [6]. Remote sensing technology [7] has become a widely used approach for burned area detection due to its ability to provide large-scale and repetitive observations [8]. Satellite imagery such as Landsat-8 [9] offers valuable information for identifying burned regions [10], [11]. However, traditional methods for burned area mapping, including threshold-based and spectral index approaches, often suffer from limitations in handling complex environmental conditions, noise, and variability in land cover [12]. Recently, deep learning (DL) techniques [13], particularly Convolutional Neural Networks (CNN) [14], have shown promising performance in image segmentation tasks [15]. Architectures such as U-Net, DeepLab, and CNN-based encoder-decoder [16] frameworks have been widely applied in remote sensing for burned area detection [17], [18]. These methods enable automatic feature extraction and pixel-level classification, improving the efficiency and scalability of burned area mapping [19]. Despite these advancements, most studies report high performance using large datasets, complex preprocessing, or additional spectral features [20], [21]. However, the performance of deep learning models on limited datasets and specific regional characteristics, such as Indonesian burned area datasets [4], remains underexplored.

This creates a research gap in understanding the robustness and generalization capability of deep learning models under constrained data conditions. Therefore, this study aims to evaluate the performance of several deep learning architectures, including DeepLab, ResNet50, ResNet101, ResNet152, and Attention U-Net, for burned area segmentation using Landsat-8 imagery. The models are trained and tested on a publicly available dataset of burned areas in Indonesia. The evaluation is conducted using standard metrics such as Intersection over Union (IoU) and Dice coefficient. The main contribution of this research is a comprehensive benchmarking and performance analysis of multiple deep learning models on a limited burned area dataset. Unlike previous studies that focus on achieving high accuracy, this study highlights the challenges and limitations of deep learning models in real-world scenarios with constrained data, providing insights for future improvements in burned area segmentation.

II. RELATED WORK

Burned area detection using remote sensing has been extensively studied using both traditional and machine learning approaches [22]. Early methods relied on spectral indices and threshold-based techniques derived from satellite imagery [23], [24]. Although effective in simple scenarios, these approaches are sensitive to noise, vegetation variability, and atmospheric conditions [25], [26]. With the advancement of artificial intelligence, machine learning methods such as Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Networks (ANN) have been applied for burned area detection and fire susceptibility mapping [21]. These methods improve classification performance but still require manual feature engineering and may struggle with complex spatial patterns. Deep learning approaches [27], particularly CNN-based models [4], [16], have recently become dominant in this field. U-Net is one of the most widely used architectures for burned area segmentation due to its encoder-decoder structure and skip connections that preserve spatial information. Several studies have reported high performance using U-Net variants, achieving high IoU and F1-scores in burned area mapping tasks. In addition to U-Net, advanced architectures such as DeepLab and Attention-based models have been proposed to improve segmentation accuracy. DeepLab utilizes atrous convolution to capture multi-scale contextual information, while Attention U-Net enhances feature representation by focusing on relevant regions in the image. Furthermore, backbone networks such as ResNet and MobileNet are often integrated into segmentation frameworks to improve feature extraction capabilities. Hybrid approaches combining CNN with other techniques have also been explored. For example, CNN combined with Random Forest (CNN-RF) [5] and models incorporating spectral indices such as NDVI and NBR have demonstrated improved performance in burned area detection [17]. Some studies also utilize multi-source data, including Sentinel-1 and Sentinel-2 imagery, to enhance model robustness. Despite these advancements, most existing studies rely on large-scale datasets, extensive preprocessing, or multi-source data fusion to achieve high performance. Limited attention has been given to evaluating model performance on small datasets with minimal preprocessing. This limitation is particularly relevant for regions where annotated data is scarce, such as Indonesia. Therefore, this study focuses on evaluating multiple deep learning architectures under constrained data conditions. By comparing DeepLab, ResNet-based models, and Attention U-Net on a limited Landsat-8 dataset, this research provides a clearer understanding of the strengths and limitations of each model for burned area segmentation.

III. MATERIALS AND METHODS

The dataset used in this study is adopted from previous research [4], which provides Landsat-8 satellite imagery for burned area analysis. Each image has a spatial dimension of 512×512 pixels and is stored in GeoTIFF format. The dataset is accompanied by ground truth segmentation masks in grayscale format. In these masks, pixel values represent two classes: burned areas are labeled with white (value=1), while non-burned areas are represented by black (value=0). These annotations were generated through manual interpretation, ensuring reliable reference data for supervised learning. The dataset is organized into four main folders, consisting of input images and corresponding ground truth masks for both training and testing phases, as summarized in Table 1. This structure allows systematic model development and evaluation.

Table 1: Research Data.

Image Landsat-8	Training	Testing	Total
Input Image 	180	47	227
Ground Truth 	180	47	227

Source: Authors, (2026).

The use of Landsat-8 imagery provides moderate spatial resolution data suitable for large-scale environmental monitoring. However, the variability in spectral characteristics and the relatively limited dataset size introduce challenges for accurate segmentation, making this dataset appropriate for evaluating the robustness of deep learning models. The overall research workflow of this study is illustrated in Figure 1. The process begins with the input of Landsat-8 satellite images, which are then divided into training and testing datasets. The training data are used to build and optimize the segmentation models, while the testing data are used to evaluate model performance. In the training phase, several deep learning architectures are implemented, including DeepLab, ResNet50, ResNet101, ResNet152, and Attention U-Net. These models are trained to learn the spatial patterns and characteristics of burned areas from the input images and corresponding ground truth masks. After the training process, the trained models are applied to the testing dataset to perform burned area segmentation. The output of this stage is a prediction map that classifies each pixel into burned or non-burned areas. Finally, the predicted segmentation results are evaluated using quantitative metrics to assess model performance. This evaluation step is crucial to compare the effectiveness of each model in detecting burned areas. The experiments in this study are conducted using a supervised learning approach for image segmentation. The dataset consists of 227 images, which are divided into 180 images for training and 47 images for testing. All models are trained using the same experimental configuration to ensure a fair comparison. The training process is performed for 30 epochs with a batch size of 2. The Adam optimizer is used with a learning rate of 0.0001 to update model weights during training. The relatively small batch size is chosen due to memory limitations and the high resolution of input images (512×512 pixels). Additionally, the limited number of training samples presents a challenge for model generalization, which is one of the key aspects analyzed in this study. During the evaluation phase, the trained models are tested on unseen data to measure their segmentation performance. The results are assessed using standard metrics such as Intersection over Union (IoU) and Dice coefficient, which are commonly used in image segmentation tasks.

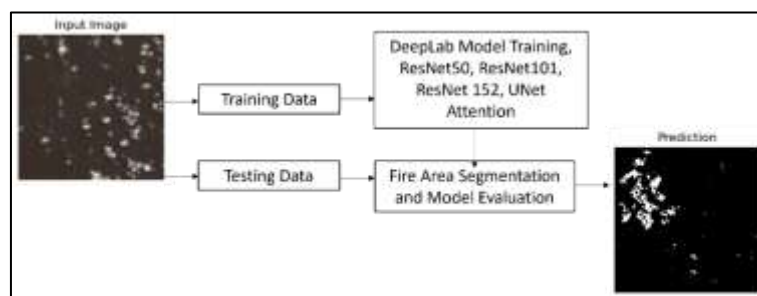


Figure 1: Research workflow for burned area segmentation.

Source: Authors, (2026).

The DeepLabV3+ architecture (Figure 2) used in this study is based on a ResNet50 backbone as the encoder for feature extraction. The network consists of two main components: an encoder with Atrous Spatial Pyramid Pooling (ASPP) and a decoder for precise segmentation. In the encoder stage, feature maps are extracted at different levels. The low-level features are obtained from the early layers of the backbone network, preserving spatial details, while high-level features are extracted from deeper layers, capturing semantic information. The ASPP module is applied to the high-level features to capture multi-scale contextual information. This module utilizes parallel atrous convolutions with different dilation rates (6, 12, and 18), along with a 1×1 convolution. These features are then concatenated and refined through additional convolutional layers. In the decoder stage, the high-level features are upsampled and combined with low-level features through skip connections. This fusion enhances spatial resolution and improves boundary segmentation. Finally, the output is upsampled to the original image size and passed through a sigmoid activation function to produce a binary segmentation map.

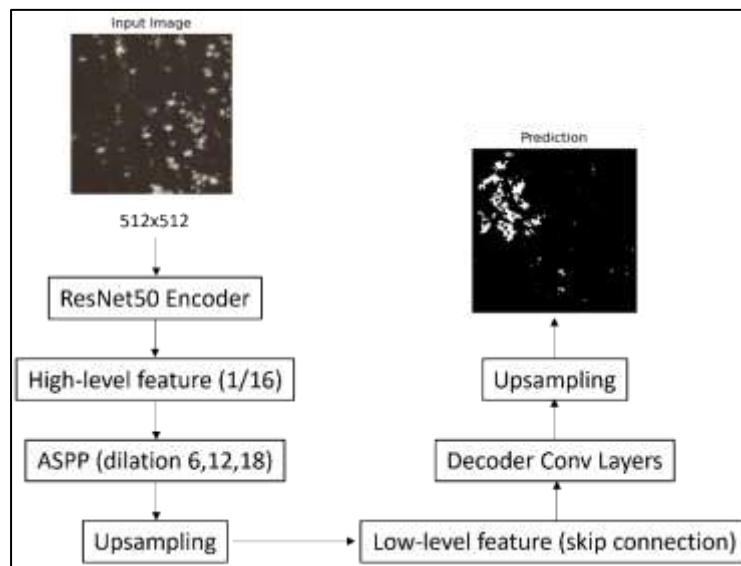


Figure 2: DeepLabV3+ architecture backbone diagram.

Source: Authors, (2026).

The ResNet50-UNet model used in this study combines the strength of the ResNet50 as an encoder and the U-Net decoder structure for semantic segmentation (Figure 3). In the encoder stage, a pre-trained ResNet50 model (trained on ImageNet) is utilized to extract hierarchical features from the input image. Several intermediate feature maps are selected as skip connections to preserve spatial information at different resolutions. Specifically, feature maps are extracted from multiple stages of the network, including early, middle, and deeper layers. The decoder stage is designed to progressively reconstruct the spatial resolution of the feature maps. The high-level features from the encoder are upsampled step by step using UpSampling layers. At each stage, the upsampled features are concatenated with the corresponding skip connections from the encoder. This fusion allows the model to combine semantic information from deeper layers with fine-grained spatial details from earlier layers. Each decoding block consists of two convolutional layers with ReLU activation to refine the feature representation. Finally, the output is upsampled to the original image size and passed through a sigmoid activation function to produce a binary segmentation map, where each pixel represents either burned or non-burned area. The segmentation model evaluation process is calculated using Jaccard and Dice similarity coefficients. Equations 1 and 2 are ways to calculate the Jaccard or Intersection over Union and Dice similarity coefficients.

$$Jaccard(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

$$Dice(A, B) = 2 * \frac{|A \cap B|}{|A| + |B|} \quad (2)$$

Description: A is the ground truth image and B is the segmentation image. The ground truth image and segmentation results have a value of 0 and 1, then the intersection value is calculated $\cap$, and union $\cup$.

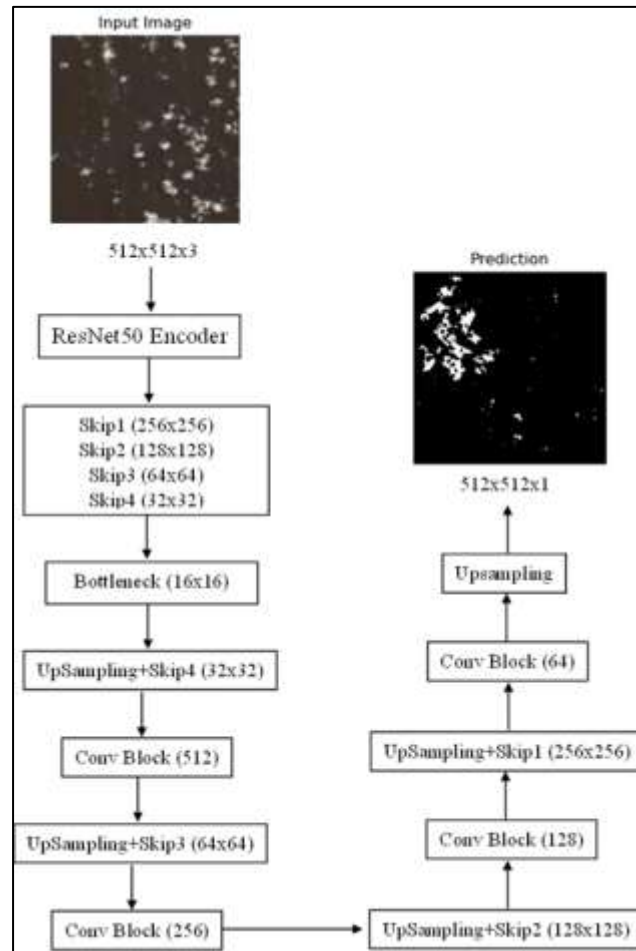


Figure 3: Architecture of the ResNet50-UNet model used for burned area segmentation.
Source: Authors, (2026).

IV. RESULTS AND DISCUSSIONS

Table 2 presents the performance comparison of the evaluated models in terms of mean Intersection over Union (IoU) and Dice coefficient for burned area segmentation. Among all tested models, the ResNet50-based U-Net achieved the best performance, with a mean IoU of 0.1939 and a Dice coefficient of 0.2645. This indicates that the model is relatively more capable of capturing burned area patterns compared to other architectures. In contrast, the DeepLab model obtained a slightly lower performance, with a mean IoU of 0.1489 and a Dice score of 0.2181.

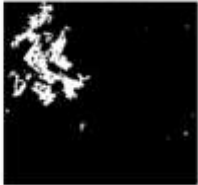
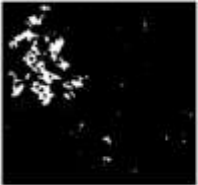
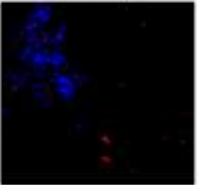
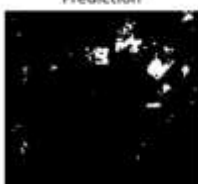
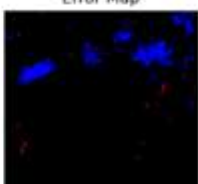
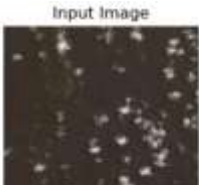
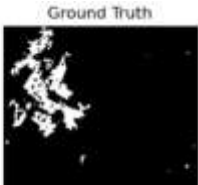
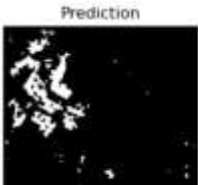
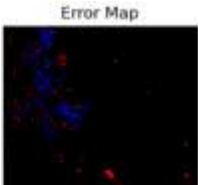
Table 2: Model Evaluation Results.

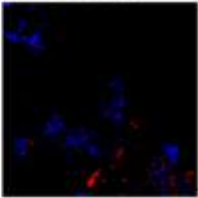
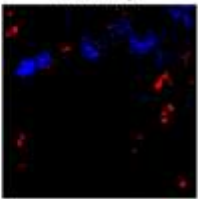
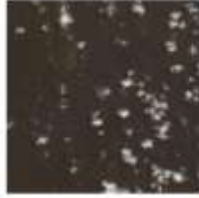
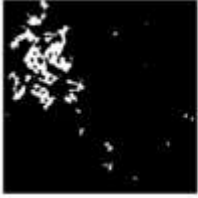
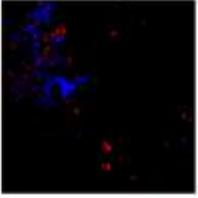
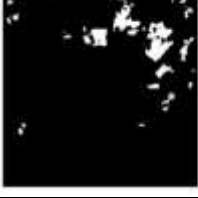
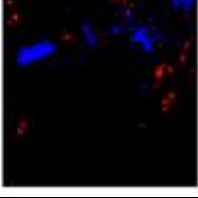
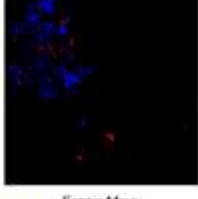
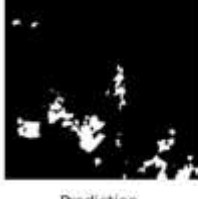
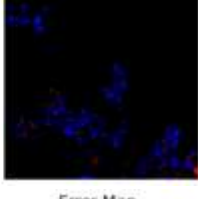
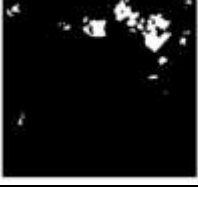
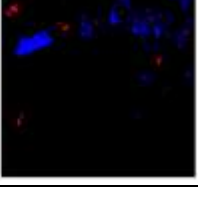
Model	Mean IoU	Mean Dice
DeepLab	0.1489	0.2181
ResNet50	0.1939	0.2645
ResNet101	0.0878	0.1363
ResNet152	0.1257	0.1857
Unet-Attention	0.0774	0.1232

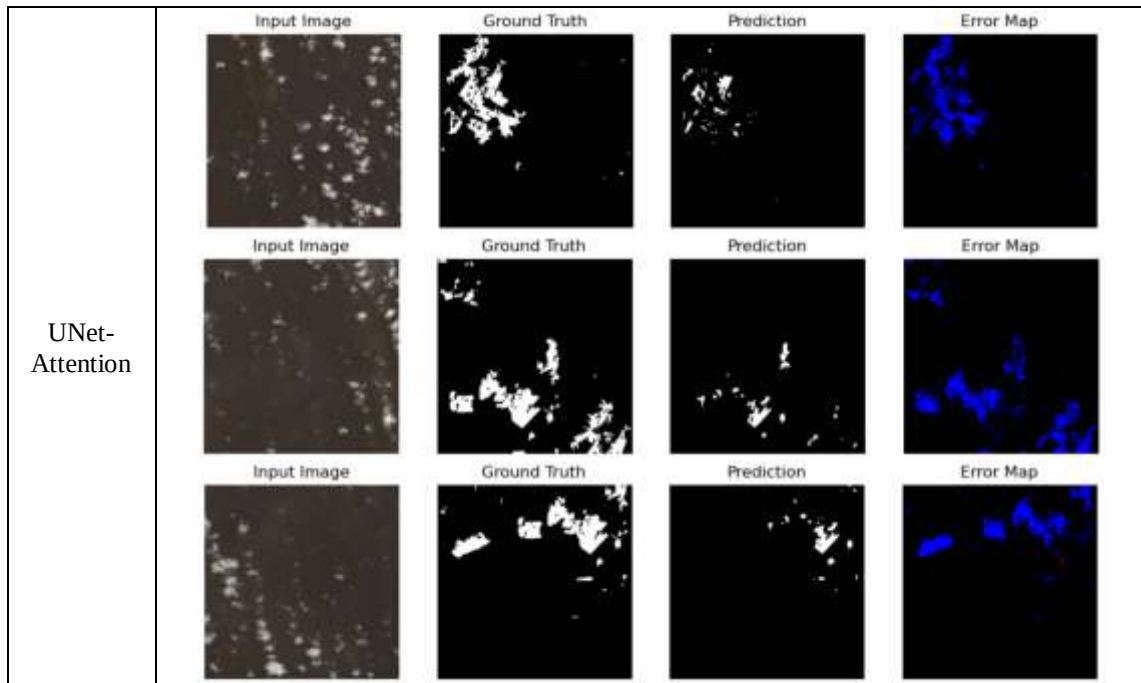
Source: Authors, (2026).

Deeper architectures, such as ResNet101 and ResNet152, did not show improved performance. ResNet101 achieved a mean IoU of 0.0878 and Dice of 0.1363, while ResNet152 reached a mean IoU of 0.1257 and Dice of 0.1857. Similarly, the Attention U-Net model produced the lowest performance among all models, with a mean IoU of 0.0774 and Dice of 0.1232. These results suggest that increasing model depth and complexity does not necessarily lead to better segmentation performance, especially when the dataset is limited. The superior performance of ResNet50 compared to deeper variants indicates that a moderate-depth architecture is more suitable for this task under constrained data conditions. Several factors may contribute to the observed performance. First, the limited size of the dataset restricts the ability of deep learning models to learn generalized features effectively. Second, the variability in burned area characteristics in Landsat-8 imagery, including differences in vegetation, burn severity, and background noise, increases the difficulty of accurate segmentation. Third, the use of only RGB channels without additional spectral indices may reduce the model's ability to distinguish burned areas from similar background patterns. Despite the relatively low performance values, this study highlights important insights regarding the applicability of deep learning models for burned area segmentation in real-world scenarios. The results emphasize that model performance is not solely determined by architectural complexity but is strongly influenced by data quality, quantity, and feature representation. Tabel 3 hasil segmentasi dari setiap model. The experimental results reveal that all evaluated models exhibit significant difficulty in accurately segmenting small burned areas. When the spatial extent of the burned region is limited, the models tend to either completely miss the burned pixels (false negatives) or produce fragmented and incomplete predictions. This behavior is primarily attributed to the strong class imbalance between burned and non-burned areas, where the background class dominates the image. In addition, deep convolutional neural networks, particularly those employing encoder-decoder architectures, inherently perform spatial downsampling during feature extraction. As a result, fine-grained details corresponding to small burned regions are often lost in deeper layers and cannot be fully recovered during the upsampling process. This leads to under-segmentation, especially along object boundaries and small isolated regions.

Table 3: Model Segmentation Results.

DeepLab	Input Image	Ground Truth	Prediction	Error Map
				
				
ResNet50	Input Image	Ground Truth	Prediction	Error Map
				
				

	Input Image  Ground Truth  Prediction  Error Map 
	Input Image  Ground Truth  Prediction  Error Map 
ResNet101	Input Image  Ground Truth  Prediction  Error Map 
	Input Image  Ground Truth  Prediction  Error Map 
	Input Image  Ground Truth  Prediction  Error Map 
ResNet152	Input Image  Ground Truth  Prediction  Error Map 
	Input Image  Ground Truth  Prediction  Error Map 
	Input Image  Ground Truth  Prediction  Error Map 



Source: Authors, (2026).

The error map further illustrates this limitation, where blue regions indicate false negatives (missed burned areas), and red regions indicate false positives (over-segmentation). The dominance of blue regions suggests that the models are more prone to missing burned areas than falsely detecting them, confirming that the models are biased toward the majority (background) class. These findings are consistent across all tested architectures, indicating that the limitation is not solely model-dependent, but also strongly influenced by dataset characteristics, particularly the small size and spatial distribution of burned regions.

V. CONCLUSIONS

This study presents a comparative evaluation of several deep learning models, namely DeepLab, ResNet50, ResNet101, ResNet152, and Attention U-Net, for burned area segmentation using Landsat-8 satellite imagery. The experimental results indicate that all models exhibit limited performance in accurately segmenting burned areas, with the highest performance achieved by the ResNet50-based model, reaching a mean IoU of 0.1939 and a Dice coefficient of 0.2645. The qualitative and quantitative analyses reveal that the models struggle particularly with small and fragmented burned areas. Most models tend to produce under-segmentation, as indicated by the dominance of false negatives, while also generating some false positives due to background confusion. This limitation is primarily attributed to class imbalance, where non-burned areas dominate the dataset, as well as the loss of fine spatial information during the downsampling process in deep neural networks. Furthermore, increasing model depth, as observed in ResNet101 and ResNet152, does not necessarily improve segmentation performance, suggesting that deeper architectures are not always suitable for datasets with limited size and high spatial complexity. Overall, this study highlights that the main challenge in burned area segmentation lies not only in model selection but also in dataset characteristics, particularly the small size and distribution of burned regions. Future work should focus on improving segmentation performance for small objects through advanced techniques such as multi-scale feature extraction, attention mechanisms, and loss functions that address class imbalance.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Nur Nafiiyah and Salwa Nabilah.

Methodology: Nur Nafiiyah and Achmad Nizar Hidayanto.

Investigation: Achmad Nizar Hidayanto.

Discussion of results: Nur Nafiiyah and Rifky Aisyatul Faroh.

Writing – Original Draft: Nur Nafiiyah, Rifky Aisyatul Faroh and Salwa Nabilah.

Writing – Review and Editing: Nur Nafiiyah and Achmad Nizar Hidayanto.

Supervision: Achmad Nizar Hidayanto.

Approval of the final text: Nur Nafiiyah, Rifky Aisyatul Faroh, Salwa Nabilah and Achmad Nizar Hidayanto.

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VIII. REFERENCES

- [1] Y. Demirel and T. Türk, "Automatic detection of active fires and burnt areas in forest areas using optical satellite imagery and deep learning methods," *Mersin Photogrammetry Journal*, vol. 6, no. 2, 2024, doi: 10.53093/mephoj.1575877.
- [2] S. T. Seydi, M. Hasanlou, and J. Chanussot, "A Quadratic Morphological Deep Neural Network Fusing Radar and Optical Data for the Mapping of Burned Areas," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 15, 2022, doi: 10.1109/JSTARS.2022.3175452.
- [3] A. Ouahab, "A deep learning model to classify forest fires burned areas using sentinel-2 data in Algeria.," *Journal of Engineering and Technology for Industrial Applications*, vol. 11, no. 55, 2025, doi: 10.5935/jetia.v11i55.2666.
- [4] Y. Prabowo et al., "Deep Learning Dataset for Estimating Burned Areas: Case Study, Indonesia," *Data (Basel)*, vol. 7, no. 6, 2022, doi: 10.3390/data7060078.
- [5] D. Sudiana et al., "A Hybrid Convolutional Neural Network and Random Forest for Burned Area Identification with Optical and Synthetic Aperture Radar (SAR) Data," *Remote Sens. (Basel)*, vol. 15, no. 3, 2023, doi: 10.3390/rs15030728.
- [6] F. H. Maskouni and S. T. Seydi, "Forest Burned Area Mapping Using Bi-Temporal Sentinel-2 Imagery Based on a Convolutional Neural Network: Case Study in Golestan Forest †," *Engineering Proceedings*, vol. 10, no. 1, 2021, doi: 10.3390/ecsa-8-11291.
- [7] H. Xu et al., "Immediate assessment of forest fire using a novel vegetation index and machine learning based on multi-platform, high temporal resolution remote sensing images," *International Journal of Applied Earth Observation and Geoinformation*, vol. 134, 2024, doi: 10.1016/j.jag.2024.104210.
- [8] R. Guo, J. Yan, H. Zheng, and B. Wu, "Assessment of the Analytic Burned Area Index for Forest Fire Severity Detection Using Sentinel and Landsat Data," *Fire*, vol. 7, no. 1, 2024, doi: 10.3390/fire7010019.
- [9] G. H. de Almeida Pereira, A. M. Fusioka, B. T. Nassu, and R. Minetto, "Active fire detection in Landsat-8 imagery: A large-scale dataset and a deep-learning study," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 178, 2021, doi: 10.1016/j.isprsjprs.2021.06.002.
- [10] A. K. Brand and A. Manandhar, "Semantic segmentation of burned areas in satellite images using a u-net-based convolutional neural network," in *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 2021. doi: 10.5194/isprs-archives-XLIII-B3-2021-47-2021.
- [11] P. Liu, Y. Liu, X. Guo, W. Zhao, H. Wu, and W. Xu, "Burned area detection and mapping using time series Sentinel-2 multispectral images," *Remote Sens. Environ.*, vol. 296, 2023, doi: 10.1016/j.rse.2023.113753.
- [12] H. M. Meimand, J. Chen, D. Kneeshaw, M. Bakhtyari, and C. Peng, "Burned Area Detection in the Eastern Canadian Boreal Forest Using a Multi-Layer Perceptron and MODIS-Derived Features," *Remote Sens. (Basel)*, vol. 17, no. 13, 2025, doi: 10.3390/rs17132162.
- [13] C. Lai, S. Zeng, W. Guo, X. Liu, Y. Li, and B. Liao, "Forest Fire Prediction with Imbalanced Data Using a Deep Neural Network Method," *Forests*, vol. 13, no. 7, 2022, doi: 10.3390/f13071129.
- [14] B. Kim, K. Lee, and S. Park, "Burned-Area Mapping Using Post-Fire PlanetScope Images and a Convolutional Neural Network," *Remote Sens. (Basel)*, vol. 16, no. 14, Jul. 2024, doi: 10.3390/rs16142629.
- [15] S. T. Seydi, M. Hasanlou, and J. Chanussot, "Burnt-Net: Wildfire burned area mapping with single post-fire Sentinel-2 data and deep learning morphological neural network," *Ecol. Indic.*, vol. 140, 2022, doi: 10.1016/j.ecolind.2022.108999.
- [16] S. T. Seydi, V. Saeidi, B. Kalantar, N. Ueda, and A. A. Halin, "Fire-Net: A Deep Learning Framework for Active Forest Fire Detection," *J. Sens.*, vol. 2022, 2022, doi: 10.1155/2022/8044390.
- [17] M. H. Calp and U. Kose, "Estimation of burned areas in forest fires using artificial neural networks," *Ingeniería Solidaria*, vol. 16, no. 3, 2020, doi: 10.16925/2357-6014.2020.03.08.
- [18] M. Prakash, S. Neelakandan, M. Tamilselvi, S. Velmurugan, S. Baghavathi Priya, and E. Ofori Martinson, "Deep Learning-Based Wildfire Image Detection and Classification Systems for Controlling Biomass," *International Journal of Intelligent Systems*, vol. 2023, 2023, doi: 10.1155/2023/7939516.
- [19] C. Lee et al., "Machine Learning-Based Forest Burned Area Detection with Various Input Variables: A Case Study of South Korea," *Applied Sciences (Switzerland)*, vol. 12, no. 19, 2022, doi: 10.3390/app121910077.
- [20] O. Kantarcioglu, S. Kocaman, and K. Schindler, "Artificial neural networks for assessing forest fire susceptibility in Türkiye," *Ecol. Inform.*, vol. 75, 2023, doi: 10.1016/j.ecoinf.2023.102034.
- [21] L. K. Sharma, R. Gupta, and N. Fatima, "Assessing the predictive efficacy of six machine learning algorithms for the susceptibility of Indian forests to fire," *Int. J. Wildland Fire*, vol. 31, no. 8, 2022, doi: 10.1071/WF22016.
- [22] L. Wang, H. Zhang, Y. Zhang, K. Hu, and K. An, "A Deep Learning-Based Experiment on Forest Wildfire Detection in Machine Vision Course," *IEEE Access*, vol. 11, 2023, doi: 10.1109/Access.2023.3262701.
- [23] M. Nolde, S. Plank, and T. Riedlinger, "An adaptive and extensible system for satellite-based, large scale burnt area monitoring in near-real time," *Remote Sens. (Basel)*, vol. 12, no. 13, 2020, doi: 10.3390/rs12132162.
- [24] A. Rostami, R. Shah-Hosseini, S. Asgari, A. Zarei, M. Aghdami-Nia, and S. Homayouni, "Active Fire Detection from Landsat-8 Imagery Using Deep Multiple Kernel Learning," *Remote Sens. (Basel)*, vol. 14, no. 4, 2022, doi: 10.3390/rs14040992.
- [25] M. İ. Gürsoy, O. Orhan, and S. Tekin, "Creation of wildfire susceptibility maps in the Mediterranean Region (Turkey) using convolutional neural networks and multilayer perceptron techniques," *For. Ecol. Manage.*, vol. 538, 2023, doi: 10.1016/j.foreco.2023.121006.
- [26] A. S. Nur, Y. J. Kim, and C. W. Lee, "Creation of Wildfire Susceptibility Maps in Plumas National Forest Using InSAR Coherence, Deep Learning, and Metaheuristic Optimization Approaches," *Remote Sens. (Basel)*, vol. 14, no. 17, 2022, doi: 10.3390/rs14174416.
- [27] G. Zhang, M. Wang, and K. Liu, "Deep neural networks for global wildfire susceptibility modelling," *Ecol. Indic.*, vol. 127, 2021, doi: 10.1016/j.ecolind.2021.107735.