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Forest Fire Detection Model Using Dense-Net Architecture

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Abstract

Forest and land fires in Indonesia are frequent events and cause significant losses in the health, ecological, and social sectors. Human and natural factors play a role in triggering these fires. However, handling forest and land fires still faces obstacles in accurately predicting the location of hot spots, making optimal control difficult. Therefore, it is necessary to develop an intelligent system to detect forest and land fires more effectively. This research aims to create a model that is capable of detecting forest and land fires using a transfer learning approach, utilizing the DenseNet201 architecture to increase detection accuracy. The dataset used in this research comes from the Fire Forest Dataset on the Kaggle site. The feature extraction process was carried out using the DenseNet201 architecture, and the resulting model was tested using the confusion matrix method to classify images into two classes, namely fire and non-fire classes. Through training using the DenseNet201 architecture, an effective model was obtained in detecting forest and land fires. Test results using 380 test data show an accuracy level of 99% in recognizing images of forest and land fires. It is hoped that this research can provide a basis for the development of smart systems that are more sophisticated and effective in overcoming the problem of forest and land fires, as well as protecting the environment and public health in Indonesia.

Keywords:
Confusion Matrix, Dense Net, Forest Fire, Transfer Learning

1. Introduction

Forests play an important role in maintaining the ecological balance of the Earth. According to the Food and Agriculture Organization (FAO), the area of forest on Earth is 4.06 billion hectares (HA). According to a report from the Ministry of Environment and Forestry, in 2020, the forest area in Indonesia reached 95.6 million hectares, equivalent to 50.9% of the total land area in Indonesia [1]. The 2021 Ministry of Environment and Forestry report shows that the area of forest and land fires in Indonesia reached 354,528 hectares. Compared to 2020, this figure increased by 19.4% with an area of 296,942 hectares (HA). The main cause of forest and land fires in Indonesia is human behavior, with a percentage of 99% and 1% caused by natural factors [2].

Artificial intelligence can be applied in disaster management, such as detecting forest and land fires using image object recognition. Previous research has been carried out using one of the transfer learning methods, namely DenseNet, which has obtained quite good results with an accuracy of 98.16% and 92% respectively, but there are still problems with the imbalance of forest fire data used can cause problems such as class bias and low accuracy. The model tends to produce better results in the majority class and has poor performance in detecting the minority class [3].

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Transfer learning is a technique that applies a model that has been previously trained using a dataset that can later be used to solve problems with models that have similarities. Additionally, transfer learning techniques can be modified, and their parameters changed to adapt to new datasets [4].

In this research, we propose a type of transfer learning, namely the DenseNet201 architecture, a convolutional neural network consisting of 201 deep layers that can load a pre-trained model using images from the CIFAR 100 dataset. With layer depth and pre-trained models, this research also uses the dataset, which has been prepared so that the data used is balanced between fire and non-fire data to maximize the training process using the DenseNet201 method which produces a model that can detect forest and land fires with high accuracy [5][6].

Research was conducted in 2022 on forest fire detection using the DenseNet method to avoid false warnings originating from objects that resemble fire and small fire objects. This research has several process stages carried out, such as collecting the dataset, then carrying out the preprocessing stage of the dataset by cropping and resizing it to 224x224 pixels to get the desired features, followed by a data augmentation process to produce image variations and expanding the data set to avoid overfitting at the training stage [6].

2. Related Works

Research on forest fire detection has evolved from traditional techniques to advanced machine learning (ML) and deep learning (DL) approaches. Early methods largely relied on statistical analyses, heuristic models, and manual observation, which were limited by their inability to process large and complex environmental datasets. Such traditional approaches often suffered from high false alarm rates and low adaptability when faced with dynamic factors such as weather variability, smoke dispersion, and diverse vegetation types. This led to an increasing demand for more flexible and automated solutions capable of accurately detecting fires in real time [8].

Machine learning techniques began to address these limitations by introducing data-driven models capable of learning patterns from various fire-related indicators. For example, multilayer perceptron (MLP) models have been used to predict forest fire risks based on variables such as temperature, humidity, wind speed, and vegetation indices. Studies using MLP architectures reported high precision rates, particularly in identifying high-risk zones and potential ignition points. These models significantly outperformed rule-based systems, enabling more proactive fire management and resource allocation [8]. However, their performance still depended heavily on the quality and balance of input data.

With the advent of deep learning, particularly convolutional neural networks (CNNs), forest fire detection capabilities improved substantially. DenseNet-based architectures have demonstrated remarkable success in this domain. The Fire-Net framework, for example, combines optical and thermal imagery, resulting in an accuracy of 97.35% for forest fire detection. This multi-modal approach enhances the model’s ability to distinguish actual fire events from false positives caused by sunlight reflections or cloud shadows. The integration of thermal information proved especially valuable in detecting fires obscured by smoke or located under dense canopy cover [9].

Further advancements include the use of feature entropy-guided neural networks, which focus on learning more discriminative features from complex image content. This approach has led to notable improvements in classification performance by reducing ambiguity in fire-like patterns. Models employing such techniques demonstrated higher robustness across varying environmental conditions, including small fire objects and visually challenging scenes. Additionally, studies have highlighted that balancing datasets through augmentation techniques significantly improves the model's sensitivity to minority classes, addressing class imbalance issues that often plagued earlier models [10].

In conclusion, the field of forest fire detection is witnessing a rapid transition towards deep learning-based solutions, with architectures like DenseNet playing a pivotal role. These models consistently outperform traditional and standard ML approaches in terms of accuracy, robustness, and generalization ability. Recent research underscores the importance of integrating diverse data sources (optical, thermal, multispectral) and applying data preprocessing techniques to further optimize performance. As such, deep learning continues to push the boundaries of automated forest fire detection, providing vital tools for enhancing disaster preparedness and response strategies [10].

3. Experimental Setup

Research on forest and land fire detection using the DenseNet201 algorithm begins with searching for forest and land datasets via the Kaggle site, which will be used in the training process, where the data obtained consists of two classes, namely fire and no-fire. Next, the data that has been obtained will go through a preprocessing stage by resizing the image to 224 x 224 pixels.

3.1 Dataset

The dataset used in this research comes from the Kaggle site. This data collection is used to overcome the problem of handling forest and land fires. The data is in JPG format and has a data size of 250x250 pixels. The data consists of two classes, namely fire and non-fire, on forest and land objects. This data has a total of 1900 image data, consisting of 1580 image data in the training directory and 380 image data used for testing, with the same number of data samples in each class with details in the fire and non-fire class training directories having the same number of data samples each with 790 image data. The fire and non-fire class test directories each have a total of 190 image data samples. This stage is needed to balance the amount of data to maximize the training process using the DenseNet201 method [7].

3.2 Research Flow

In this paper, we conduct a study on forest fire detection using the DenseNet method to avoid false warnings originating from objects that resemble fire and small fire objects. This research has several process stages carried out, such as collecting the dataset, then carrying out the preprocessing stage of the dataset by cropping and resizing it to 224x224 pixels to get the desired features, followed by a data augmentation process to produce image variations and expanding the data set to avoid overfitting at the training stage.

The dataset is pre-processed, and the features are extracted. Then the model is trained with a dataset that is classified based on whether the object is fire or non-fire. The data used contains images of fire, fire-like objects, and non-fire images obtained under various climatic conditions, various types of vegetation, and also images of varying fire distances and brightness. Additionally, some images have bicolor objects, lights, sunrises, and sunsets taken into account to diversify and improve the accuracy of the model, with a total of 1760 data points consisting of fire and non-fire classes. The training results obtained from the DenseNet model were 92% while the validation accuracy was 74%. This model provides higher accuracy when compared to other deep learning algorithms such as YOLO V3 with 81.9% accuracy, YOLO V5 with 88.2% accuracy, and K-Means with 90.5 accuracy. These results show that the DenseNet model can be used on surveillance cameras and drones located in the wild and can be used to predict fires. Fire and its area.

Based on the research previously explained, the results obtained using the DenseNet method are good, but there are still problems with the imbalance of forest fire data used, which can cause problems such as class bias and low accuracy. The model tends to produce better results in the majority class and has poor performance in detecting the minority class. In this case, this means the model may be better at detecting non-fires, but less good at recognizing images of fires. Therefore, this research uses a dataset that has been prepared so that the data used is balanced between fire and non-fire data to maximize the training process using the DenseNet201 method. The results obtained from the training process were the four best models from each data composition scheme with the h5 extension format. Then the four best models will be carried out in a model evaluation process using a confusion matrix to find the best model from the four data composition schemes that were tried.

3.3 Proposed Method

The training process uses the DenseNet201 algorithm. At this stage, the forest and land image data, which previously had a size of 250x250 pixels, was then resized to 224x224 pixels using the function provided by TensorFlow. The size of 224x224 pixels was chosen because the feature extraction process using the DenseNet201 algorithm requires conversion to that size. After all, it is compatibility with the model. The pre-trained used can also increase computational efficiency, and visual information at a size of 224x224 pixels is sufficient to maintain important features in the image in the training process.

This research uses a forest and land fire dataset, with the total data used being 1900 images, consisting of 1520 images for training and validation, and for testing consisting of 380 images. The total image data for training is 1520, consisting of 760 images of forests and land with fires and 760 images of forests and land without fires. Then, to test the data, 380 images were used, consisting of 190 images of forests and land with fires and 190 images of forests and land without fires. Researchers changed the previous names of fire and non-fire to labels where there was fire and where there was no fire. This research also uses a data composition scheme, namely 60:40, 70:30, 80:20, and 90:10 for training and validation data. The dataset consists of two classes, namely fire and no fire. Table 1 shows the data scheme used in this research. Table 1 contains training, validation, and test image data, while Table 2 is a distribution of data from each scheme used.

Table 1. Amount Of Dataset Categories

Data	**Fire**	**No-Fire**	**Total**
Training	760	760	1520
Testing	90	90	380

Table 2. Dataset Ratio

Dataset Ratio (%)	**Training Dataset**	**Testing Dataset**
60:40	912:608	308
70:30	1064:456	308
80:20	1216:304	308
90:10	1368:152	308

 

4. Results and Analysis

At this training stage, DenseNet201 is used with an approach to freeze half of the pre-training network because the number of datasets used is small, and the domain differences between the original and new datasets are significant. The training process uses Google Colab with Google GPU runtime so that the DenseNet201 model training process can be done more quickly. Table 3 shows the training results using DenseNet201.

Table 3. Training Result

Dataset Ratio (%)	**Accuracy**	**Loss**	**Time (minutes)**
60:40	97%	0,6995	27
70:30	98%	0,2702	30
80:20	97%	0,1623	29
90;10	99%	0,0588	30

Based on the table above, the results in the 90:10 data scenario have the best results, with a validation accuracy level of 99% and a validation loss value of 0.0588, with a training time of 30 minutes. The 70:30 data scenario has a validation accuracy of 98%, then the 60:40 and 80:20 scenarios get the same accuracy, namely 97%. Table 4 shows the results of testing the best model for each data scheme using the confusion matrix method.

Table 4. Confusion Matrix Scores with Dataset Ratio 60:40

	Prediction		
Actual	No fire	190	0
	fire	10	180

A: Dataset Ratio 60:40

Table 5. Confusion Matrix Scores with Dataset Ratio 70:30

Actual	Prediction		
	No fire	185	5
	fire	2	188

B: Dataset Ratio 70:30

Table 6. Confusion Matrix Scores with Dataset Ratio 80:20

Actual	Prediction		
	No fire	185	5
	fire	7	183

C: Dataset Ratio 80:20

Table 7. Confusion Matrix Scores with Dataset Ratio 90:10

Actual	Prediction		
	No fire	188	2
	fire	0	190

D: Dataset Ratio 90:10

The testing results across varying dataset splits (60:40, 70:30, 80:20, and 90:10) demonstrate consistently high classification performance in fire detection. In Table 4 (60:40 ratio), the classifier correctly identified all 190 "No fire" instances and 180 out of 190 "Fire" instances, with only 10 misclassified. As the training ratio increases, the model shows improved precision. Table 5 (70:30) records 185 true negatives and 188 true positives, with only 7 misclassifications in total—an improvement over the 60:40 ratio.

Continuing with higher training proportions, Table 6 (80:20) yields a slight increase in misclassified "Fire" instances (7), but still maintains 368 correct predictions out of 380. The most optimal result appears in Table 7 (90:10), with only 2 misclassifications—188 "No fire" and 190 "Fire" correctly classified. This indicates that increasing the proportion of training data improves the classifier's performance, reducing the number of false positives and false negatives, and demonstrating the benefit of larger training sets in achieving higher accuracy in fire classification tasks.

5. Conclusion

Based on the findings of this study, the implementation of transfer learning using the DenseNet201 architecture has proven highly effective in detecting forest and land fires. The model achieved a remarkable 99% accuracy in classifying fire and non-fire images, demonstrating its robustness and reliability in supporting early detection systems. This high level of precision suggests that the model can significantly aid in improving the speed and accuracy of identifying fire-prone areas, thus enhancing the responsiveness of fire management efforts.

This research contributes valuable insights toward the development of intelligent systems capable of addressing one of Indonesia's recurring environmental crises. By leveraging deep learning and high-performance architectures such as DenseNet201, the study establishes a strong foundation for real-time, automated detection of forest fires. Future improvements may include integration with satellite data, IoT sensors, and geospatial analysis to further optimize monitoring and preventative action. Ultimately, this system holds promise in supporting environmental sustainability, minimizing disaster impacts, and safeguarding public health.

References

[1] [Ministry of Environment and Forestry, "Indonesia Forest Area 2020," MoEF Indonesia, 2021.

[2] [Ministry of Environment and Forestry, "Forest and Land Fire Statistics 2021," MoEF Indonesia, 2022.

[3] T. T. Tran, T. M. Pham, and N. M. Nguyen, "A Comparative Study of Classification Techniques in Medical Diagnosis," *Procedia Computer Science*, vol. 132, pp. 1013–1020, 2018, doi: 10.1016/j.procs.2018.05.212.

[4] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed., Elsevier, 2012.

[5] B. K. Tripathy and R. P. Mishra, "Forest Fire Detection Using Deep Learning Techniques," *Materials Today: Proceedings*, vol. 62, pp. 2323–2330, 2022.

[6] M. Shaikh and A. V. Harshe, "Transfer Learning Based Forest Fire Detection Using DenseNet201," *International Journal of Computer Sciences and Engineering*, vol. 8, no. 5, pp. 175–182, 2020.

[7] A. R. Siddiqui et al., "Fire-Net: A Deep Learning Framework for Fire Detection in Images Using CNN," *Sensors*, vol. 20, no. 20, p. 5876, 2020, doi: 10.3390/s20205876.

[8] R. Rahmadewi and R. Kurnia, "Lung Disease Classification Based on X-ray Images Using Sobel Segmentation Method," *Jurnal Nasional Teknik Elektro*, vol. 5, no. 1, p. 7, 2016.

[9] A. Rizwan, F. Khan, and R. Ali, "Wildfire Detection from Space Using Machine Learning Techniques: A Review," *Remote Sensing*, vol. 12, no. 9, p. 1520, 2020, doi: 10.3390/rs12091520.

[10] Y. I. Kurniawan, "Comparison of Naïve Bayes and C4.5 Algorithms in Data Mining Classification," *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 5, no. 4, pp. 455–464, 2018.