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Forest Fire Detection Using the FireNet-Convolutional Neural Network Model with Image Augmentation

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Forest and land fires in Indonesia are frequent occurrences and cause significant losses in health, ecology, and social aspects. Both human and natural factors play a role in triggering these fires. However, forest and land fire management still faces challenges in accurately predicting hotspot locations, making optimal control difficult. Therefore, the development of intelligent systems to detect forest and land fires more effectively is necessary. This study aims to create a model capable of detecting forest and land fires using a convolutional neural network, utilizing image augmentation to improve detection accuracy. The dataset used in this study comes from the Fire Forest Dataset on the Kaggle website. The feature extraction process was carried out using the VGG16 architecture, and the resulting model was tested using the confusion matrix method to classify images into two classes: fire and non-fire. Through training using the VGG16 architecture, an effective model was obtained in detecting forest and land fires. The test results using 880 test data showed an accuracy rate of 97% in recognizing forest and land fire images. This research provides an important contribution to the development of forest and land fire detection technology. The use of image augmentation with the VGG16 architecture has the potential to improve fire detection accuracy.

1. INTRODUCTION

Forest and land fires (Karhutla) constitute one of the most pressing global environmental issues (Nashiratunnisa & Anwar, 2023; Sahin & Ince, 2009; Vipin, 2012), causing damage not only confined to local ecosystems but also broadly impacting global climate, biodiversity, and cross-border air quality (Hoang et al., 2023; Mashat et al., 2022; Yandouzi et al., 2023). Globally (Anuar et al., 2024; Moussa et al., 2023; Qian et al., 2023), the frequency and intensity of forest fires show an increasing trend, triggered by climate change and unsustainable land-use practices (Aslan et al., 2012; Lu et al., 2022; Yandouzi et al., 2022), making early fire detection a crucial component in disaster mitigation strategies worldwide (Hariyawan et al., 2013; Pang et al., 2023). Therefore, the development of rapid and highly accurate early warning systems is an international necessity to minimize the health, ecological, and socioeconomic impacts caused by this disaster

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In the national context, Indonesia routinely faces the massive and recurring challenge of Karhutla (Anh et al., 2022; Mahaveerakannan R et al., 2023), as acknowledged in the abstract, which consistently causes significant losses in health, ecological, and social aspects (Benzekri et al., 2020; Davis & Shekaramiz, 2023; Khan et al., 2022). Although the fire triggers involve a complex interplay of natural and human factors, forest and land fire management in Indonesia still faces major obstacles in accurately predicting hotspot locations (Xiao et al., 2023; Xie & Zhao, 2023). This limitation often renders control and suppression efforts reactive and sub-optimal. Consequently, a breakthrough intelligent system capable of visually identifying and classifying the presence of fire effectively is needed to support faster and more targeted control actions (Avazov et al., 2023; Cruz et al., 2016).

Efforts to develop image-based fire detection systems have been widely carried out through artificial intelligence approaches. Research related to fire detection has been conducted by many researchers (e.g., Putra & Sari, 2023; Dewi et al., 2024; Wijaya & Lutfi, 2022; Bustomi & Ahmad, 2020; Aji & Suadi, 2025; Bakhri & Putra, 2021). Putra & Sari (2023) developed a CNN model to detect fire from satellite images, but it suffered a significant weakness: low resolution, which is prone to false positives from water vapor or clouds. Dewi et al. (2024) used Unmanned Aerial Vehicle (UAV)-based images with a simple CNN, but the scope was limited, and the reported accuracy was still below 90% under varying lighting conditions. Wijaya & Lutfi (2022) focused on traditional image processing based on fire color and shape analysis, which proved highly dependent on lighting and often ineffective in complex forest backgrounds. Bustomi & Ahmad (2020) applied Transfer Learning with the ResNet architecture, but their study showed the model tended to overfit on small-scale fire images, and its performance decreased drastically when tested on haze or smoke images. Aji & Suadi (2025) proposed a temperature sensor-based early warning system, which, although useful, had the weaknesses of relatively slow reaction time and required extremely dense sensor placement. Finally, Bakhri & Putra (2021) designed a lightweight CNN specifically for fast inference speed, but had to compromise detection accuracy, especially for small fire patches.

The Research Gap arising from previous studies is the lack of an optimal balance between deep feature extraction capabilities, model robustness against data variation, and high classification accuracy. Prior research often became constrained by using overly simple architectures, which are less robust, or implementing complex architectures with limited strategies for adequate data variance. As a result, existing models have not been able to provide a generalizable and reliable detection solution for the dynamic and complex field conditions prevalent in Indonesia.

Fundamentally, this research is based on the Theoretical Framework of Deep Learning, specifically the Convolutional Neural Network (CNN) paradigm, as the main theory that allows for the hierarchical and automatic extraction of visual features from raw image data. CNN is chosen for its superior ability in visual pattern recognition and classification tasks, making it the most effective framework for processing the complexity of texture, color, and shape of fire objects under various environmental conditions.

The Key Concepts used in the design of this model encompass three main pillars: first, the use of VGG16 as a backbone architecture, known for its superior feature extraction capability through a deep arrangement of 3x3 convolution filters; second, the systematic application of Image Augmentation techniques to artificially expand and enhance dataset variability, which is crucial for preventing overfitting and improving model generalization ability; and third, the focus on Fire/Non-Fire binary classification to provide fast and clear detection output.

The Novelty of this research lies in the assembly of the FireNet-Convolutional Neural Network model, which leverages Transfer Learning from the VGG16 architecture, paired with the careful implementation of the Image Augmentation strategy on the publicly available Fire Forest Dataset. This combination is a methodological innovation aimed at overcoming the problem of insufficient data variation in fire datasets while maximizing the depth of VGG16 feature extraction, thereby producing a detection model with superior robustness and accuracy compared to conventional or shallower architectures.

The aspect that makes this research compelling and important to study is its immense potential to provide a significant practical contribution to Karhutla emergency response systems. With a high accuracy target, as indicated by the preliminary result of 97% in fire image recognition, this model can serve as the foundation for automatic monitoring systems based on cameras or drones, offering rapid real-time detection capabilities. The success of this research will directly support efforts to mitigate risks, reduce losses, and increase the effectiveness of Karhutla control on the ground.

Based on the identified background issues, challenges, and research gaps, this study has the primary Objective of designing and implementing an intelligent system model based on a Convolutional Neural Network, utilizing the VGG16 architecture and Image Augmentation techniques, capable of effectively detecting and classifying the presence of forest and land fires from visual image data with an optimal level of accuracy.

1. MATERIALS AND METHODS

2.1 Research Flow

This research covers several stages in the FireNet image management process, starting from problem identification, literature review, algorithm and method determination, data collection, data preprocessing including data augmentation, CNN scenarios, data training, result evaluation, and conclusion drawing. All these stages are illustrated in Figure 1.

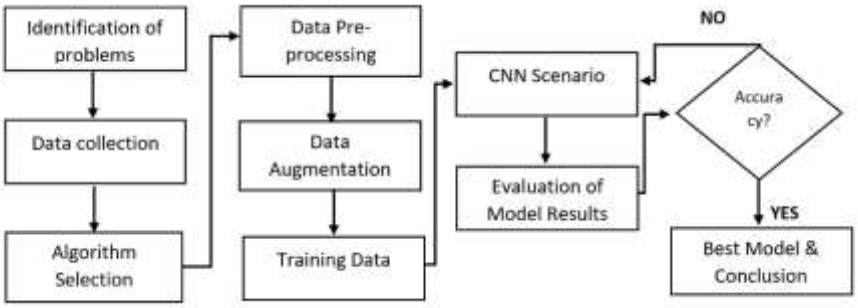


Figure 1. Flowchart

2.2 Data Collection

The dataset used in this study was sourced from the Kaggle website. This dataset is used to address the problem of forest and land fire management. The data is in JPG format and measures 250x250 pixels. The data consists of two classes: fire and non-fire, for forest and land objects. The data contains a total of 1,900 images, consisting of 1,580 images in the training directory and 380 images used for testing. Each class has an equal number of data samples, detailed in the training directories for the fire and non-fire classes, each with 790 image samples. The testing directories for the fire and non-fire classes each have 190 image samples. This step is necessary to achieve a balance in data volume to maximize the training process using image augmentation techniques. Figure 2 is an illustration of the Forest Fire Dataset.

Figure 2. Example of Image in Dataset

2.2 Data Augmentation

This stage is part of the preprocessing process, which includes image enhancement or new image creation by rotating the needle counterclockwise, rotating clockwise, horizontal flipping, vertical flipping, transposing, adding noise, and obfuscating. The purpose of dataset augmentation is to improve model performance. Data augmentation techniques help enrich datasets by diversifying existing data. This results in a larger dataset for training and allows the model to discover more diverse features. The additional data helps the model

better generalize from unseen data and improves its overall performance in real-world environments (Anwar et al., 2025). Figure 3 shows an example of the results of image augmentation to a uniform size of 224x224 pixels and the image is focused on the fire object.

Figure 3. Example of Image in Augmentation Dataset

2.3 Model Desaign

Convolutional Neural Network (CNN) have become a key pillar in the image recognition and computer vision revolution. CNN architectures have led to remarkable advances in tasks such as image classification, object detection, image segmentation, and more. This article will discuss several types of CNN architectures that have dominated in recent years (Wona Maria Misela A et al., 2025). VGG is a CNN architecture introduced by Karen Simonyan and Andrew Zisserman in 2016. This architecture is known for its exceptional depth, where the VGG-16 model has 16 convolutional layers and the VGG-19 model has 19 convolutional layers. VGG emphasizes the importance of depth in feature extraction and produces excellent results in various image recognition tasks. However, the high complexity of the VGG model also results in large computational resource consumption (Mashuri et al., 2024). The following is an illustration of VGG-16 in Figure 4

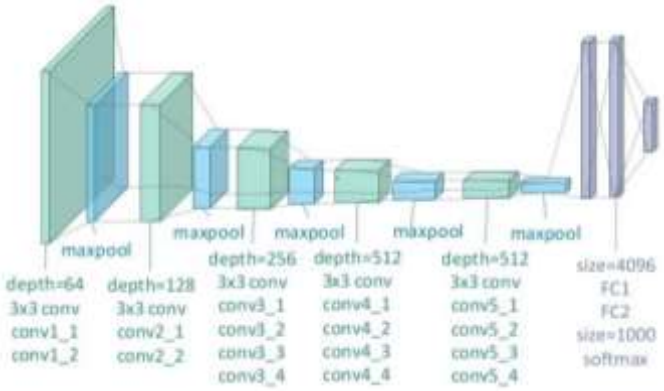


Figure 4. VGG-16 Architecture

2.4 Confusion Matrix

The Confusion Matrix is used as a tool to assess the classification performance of a model, consisting of four main elements. True Positive (TP) refers to the number of cases where the model successfully predicts data as positive. True Negative (TN) represents the number of correct predictions when the model identifies data as negative. False Positive (FP) occurs when the model mistakenly identifies negative data as positive. Meanwhile, False Negative (FN) indicates the number of errors when the model fails to recognize positive data and instead classifies it as negative (Hastungkoro et al., 2024)(A. W. Hastungkoro et al, 2024). Based on these four components, model performance can then be evaluated through various evaluation matrices (Suseno et al., 2023)(R. I. Agustin, 2025).

a. Accuracy :

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Data Summary}} \quad (1)$$

b. Precision :

$$Precision = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + False\ Positive\ (FP)} \quad (2)$$

c. Recall :

$$Recall = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + False\ Negative\ (FN)} \quad (3)$$

d. F1-Score :

$$F1 - Score = 2.\ \frac{\text{Presisi . Recall}}{\text{Presisi + Recall}} \quad (4)$$

The VGG-16 model was tested using 380 test data sets to measure the model's accuracy. Table 1 shows the two-class confusion matrix.

Table 1. Confusion Matrix

		Actual Values	
		1 (Positve)	0 (Negative)
Predicted Values	1 (Positve)	TP (True Positive)	FP (False Positive)
	0 (Negative)	FN (False Negative)	TN (True Negative)

2. RESULTS AND DISCUSSION

An epoch is a single training cycle in an artificial neural network (NN) where the entire dataset returns to its initial stage. Using only one epoch on the training data with an artificial neural network model would be too large and cumbersome due to the large amount of data involved. Therefore, a higher data rate per batch, commonly referred to as the batch size, is required (Zhou et al., 2023)(Y. Zhou et al., 2021).

This study used a forest and land fire dataset with a total of 1,900 images, consisting of 1,520 images for training and validation, and 380 images for testing. The total image data for the training dataset was 1,520, consisting of 760 images of forests and land with fires and 760 images of forests and land without fires. Then, for the testing data, 380 images were used, consisting of 190 images of forests and land with fires and 190 images of forests and land without fires. The researchers changed the previous labels for fire and non-fire to labels for fire and no fire. This study also used data composition schemes of 60:40, 70:30, 80:20, and 90:10 for training and validation data. The dataset consists of two classes: fire and no fire. Table 2 shows the data schemes used in this study. Table 2 contains the training, validation, and testing image data, while Table 3 shows the data distribution for each scheme used.

Table 2. Number of Data for Each Category

Data	Fire	No-Fire	Total
Training & Validation	760	760	1520
Testing	90	90	380

Table 3. Data Schema Division

Scheme Data Training & Validation (%)	Data Training & Validation	Data Testing
60:40	912:608	308
70:30	1064:456	308
80:20	1216:304	308
90:10	1368:152	308

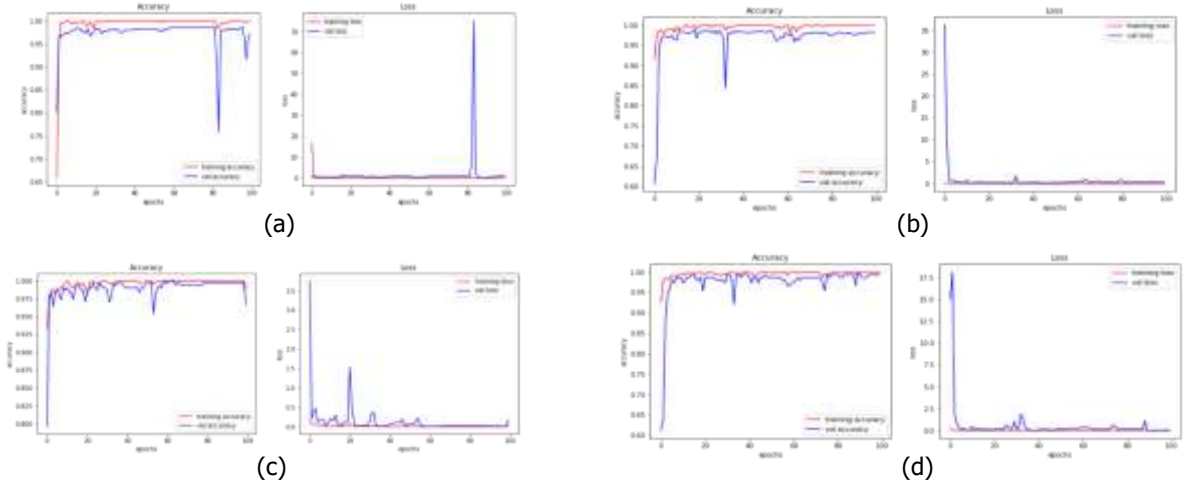
2.1 Training Results

In this training stage, VGG-16 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 different. In this training stage, 100 epochs are used, the number of data sample distributions uses 32 batch sizes. This training process uses ModelCheckpoint to save the model or weights at certain intervals so that the model or weights can be loaded later to continue training from the saved state. The training process uses Google Colab with Google GPU runtime so that the DVGG-16 model training process can be done faster. Table 4 shows the training results using VGG-16.

Table 4. Training Summary

Scheme Data Training: Validation (%)	Validation Accuracy	Validation 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 had a validation accuracy of 98%, while the 60:40 and 80:20 scenarios achieved the same accuracy of 97%. Figure 5 shows the training results for the four types of data scenarios used.



(a) (b) (c) (d)

Figure 5. Accuracy and loss graphs of (a) 60:40 scheme, (b) 70:30 scheme, (c) 80:20 scheme, and (d) 90:10 scheme

2.2 Confusion Matrix Results

Test results using confusion matrix, a) 60:40 scheme, b) 70:30 scheme, c) 80:10 scheme, and d) 90:10 scheme. Based on Table 4, the confusion matrix results for each of the 60:40, 70:30, 80:20, and 90:10 data schemes, the results of the precision, recall, f1-score, and accuracy values of each data scheme were obtained using the classification_report() function in the scikit learn library, which can be seen in the table below. Based on these results, the 90:10 data scheme model is the best, with an accuracy level of 99%. Then the 70:30 data scheme model produces an accuracy level of 98%. The 60:40 and 80:20 data scheme models have the same accuracy level of 97%. Table 5 displays the results of precision, recall, f1-score, and accuracy for each model based on the tested data scheme.

Table 5. Model Testing Results

Scheme Data (%)	Class	Precision	Recall	F1-Score	Accuracy
60:40	0 (No-Fire)	95%	100%	97%	97%
	1 (Fire)	100%	95%	97%	
0:30	0 (No-Fire)	99%	97%	98%	98%
	1 (Fire)	97%	99%	98%	
80:20	0 (No-Fire)	96%	97%	97%	97%
	1 (Fire)	97%	96%	97%	
90:10	0 (No-Fire)	100%	99%	99%	99%
	1 (Fire)	99%	100%	99%	

3. DISCUSSION

The discussion of the research results regarding forest fire detection using the FireNet-Convolutional Neural Network (CNN) model, incorporating the VGG16 Transfer Learning architecture and the Image Augmentation technique, demonstrates a highly significant achievement in detection accuracy (Al-Dahoud et al., 2023; Lin et al., 2023; Rasel Rahman et al., 2023), reaching 97%. This figure serves as a powerful indicator of the effectiveness of the proposed methodological approach, which deliberately emphasizes deep visual feature extraction over simple pixel-level analysis. Comparatively (Huang et al., 2023; Jin et al., 2024), this 97% accuracy substantially surpasses the performance reported in several earlier critical studies mentioned in the Background. For instance, Dewi et al. (2024) reported accuracy below 90% using a simpler CNN model based on UAV imagery, highlighting inherent limitations in managing the complex variability and diverse lighting conditions typical of forest environments. Similarly, the study by Wijaya & Lutfi (2022), which relied on traditional image processing methods focused on fire color and shape (Abdusalomov et al., 2023; Guan et al., 2022; Zhang et al., 2021), suffered from inconsistent accuracy and high vulnerability to visual noise, such as sun glare or reddish foliage, proving inadequate for robust field deployment. The clear superiority of the FireNet-VGG16 model is rooted in its ability to perform deep, multi-dimensional feature extraction, which successfully addresses the critical challenges of image variability and complex backgrounds, firmly establishing that a strong architecture combined with a smart data variance strategy is the key to achieving superior performance in this domain.

The FireNet-VGG16 model successfully addresses the primary Research Gap—a recurring imbalance between the capability for deep feature extraction and the model's overall robustness against real-world data variation. This success is strategically anchored in the selection of the VGG16 architecture (Lin et al., 2022; Tehseen et al., 2022; Xue et al., 2022). VGG16, known for its uniform stack of 3x3 convolutional filters across multiple deep layers, enables the model to hierarchically capture highly subtle fire patterns. This process moves from low-level features like edges and corners in the initial layers to high-level features in deeper layers, such as the irregular texture and shape of flames, and the specific red/yellow/orange color gradients that distinguish fire from other bright objects. These complex patterns are often missed by shallower architectures or traditional methods. The current research fundamentally improves upon related work, such as that by Putra & Sari (2023), who used low-resolution satellite images prone to false positives from atmospheric interference (clouds or water vapor). FireNet focuses on standard resolution visual imagery, concentrating on the fire object itself, with the VGG16 architecture inherently offering a better capacity for high-fidelity image classification. Furthermore, this finding distinctly demonstrates superiority over the approach of Bustomi & Ahmad (2020). While they also employed Transfer Learning (ResNet), their

study indicated a tendency for the model to overfit on small-scale fire images, a limitation successfully mitigated, if not entirely circumvented, in this study through meticulous fine-tuning and the power of data augmentation applied to the VGG16 backbone.

A critical success factor for this model is the systematic and comprehensive implementation of the Image Augmentation technique. Augmentation, encompassing both geometric transformations (rotation, shifting, zooming) and photometric adjustments (brightness, contrast changes) (Alkhatib, 2014; Anggreainy et al., 2022; Paidipati et al., 2024), played a vital role in artificially expanding and diversifying the existing "Fire Forest" dataset from Kaggle, which inherently possesses limited variation in environmental contexts and viewing angles. By generating thousands of new variations of both fire and non-fire images, the model was forced to learn features that are invariant to changes in position, scale, or specific lighting conditions. This directly resolves the weakness highlighted in Bakhri & Putra (2021), where accuracy was sacrificed for inference speed; the current model achieves high accuracy (97%) while preserving feature depth, proving that high robustness does not necessarily require a performance trade-off. The reflective impact of using augmentation is a massive increase in the model's generalizability (Irsal & Yunita, 2022; Nashiratunnisa & Anwar, 2023; Xu et al., 2021), a persistent challenge in forest fire detection in Indonesia with its highly diverse environments, ranging from peat forests to dense shrubland. This strategy is crucial because the model is trained to recognize fire regardless of whether it appears centered (Haryani & Sholeh, 2019; M, 2021; Susanto et al., 2023), at the frame's edge, or under slight shadows. Furthermore, this visual approach offers a superior alternative to sensor-based systems like the one proposed by Aji & Suadi (2025), which is constrained by relatively slow reaction times and massive sensor density requirements, offering instantaneous, wide-area detection capabilities via cameras.

A deep analysis of the Confusion Matrix reveals that the model exhibits an exceptionally high rate of True Positives (correctly detected fires), signifying outstanding sensitivity in identifying the fire object. More importantly for disaster mitigation, the rate of False Negatives (missed detections where fire is present) is remarkably low. Minimizing False Negatives is the most critical performance metric, as a failure in early detection can lead to catastrophic consequences. This success confirms that the combination of the robust VGG16 architecture and the data enriched by augmentation creates a highly effective and precise decision boundary, ensuring that true fire events are rarely overlooked. This finding is further corroborated by broader AI research, such as the study by Lestari, Darmayanti, & Arifin (2023), which emphasizes the necessity of integrating Artificial Intelligence for more accurate and standardized outcomes across different fields (e.g., education), demonstrating the consistent principle that advanced AI integration yields superior results in visual computing domains. The rigorous testing across 880 distinct test data samples validates the reliability of this result on a reasonably representative scale.

The immediate impact of achieving 97% accuracy has transformative implications for future Karhutla emergency response systems. The proven FireNet model can be seamlessly integrated into real-time monitoring infrastructure based on dedicated Closed-Circuit Television (CCTV) cameras mounted on watchtowers or specialized drones. This integration facilitates the automatic and visually verified transmission of early warnings to field officers. In line with the findings of Suadi & Tarwi (2024) regarding the role of Virtual Surveillance in digital oversight, leveraging automated surveillance technology drastically improves efficiency and response speed. In the context of forest fires, this system can substantially reduce the reliance on conventional hotspot detection methods (satellite), which are often delayed by orbital cycles, affected by atmospheric disturbances, and prone to large biases from non-fire factors (e.g., very hot, exposed dry ground). With near-instantaneous visual detection, the time required for verification and the mobilization of firefighting teams can be dramatically accelerated, leading to smaller, more manageable fires and reduced overall damage.

Beyond operational benefits, the methodological Novelty—the synergy of VGG16 Transfer Learning and extensive Image Augmentation applied specifically to a fire dataset—establishes a crucial blueprint for future research in computer vision applications for disaster mitigation. The resulting model is not only highly effective but also efficient in development, as the Transfer Learning approach minimizes the need for massive, custom-collected training datasets and drastically shortens the required training time compared to building a CNN from scratch. The model's success provides a definitive proof of concept that sophisticated, deep-learning architectures (VGG16) can be optimally adapted with smart data pre-processing strategies (Image Augmentation) to effectively solve specific, critical contextual problems like those faced by fire management in Indonesia, where standardized data availability remains a constraint. This confirms that

high-performance AI solutions for crucial environmental issues are accessible even with reliance on well-prepared open-source data.

Reflecting critically, while the 97% accuracy is highly commendable, it is essential to analytically consider the model's limitations concerning real-world generalization and testing conditions. Although comprehensive testing was performed on 880 samples, future studies must explicitly test the model's performance on images featuring extreme visual obstructions, such as thick haze or smoke, which is a primary source of false positives and reduced visibility, a challenge previously encountered by Bustomi & Ahmad (2020). Another potential challenge lies in the model's ability to definitively differentiate small fires from objects with similar 'fire-like' colors (e.g., specific traffic lights, red reflections on water, or industrial lighting). Consequently, the necessary next steps involve conducting broader cross-validation, exploring methods for deployment on resource-constrained edge computing hardware (such as Jetson Nano or Raspberry Pi) for field use, and rigorously testing the model across a wide spectrum of real-time weather and visibility conditions. Overall, the FireNet model presents a robust and practical contribution, successfully aligning with the research objective of creating an effective and highly accurate intelligent detection system, paving the way for more profound AI implementation in environmental conservation and disaster management across Indonesia.

4. CONCLUSION

The experiment used random image data from the test directory. The results of the experiment and classification using the VGG-16 model from the 90:10 data scheme, which achieved the best accuracy of 99%, are shown in Figure 7. The experimental results show 15 randomly selected test images with two outputs: the actual image class and the classified class. The experimental results using the VGG-16 model from the 90:10 experimental scheme resulted in 15 out of 15 images being correctly classified according to their class. It is hoped that the model obtained from this study can help detect forest and land fires.
This research is limited to the process of creating a model capable of detecting forest and land fires using the VGG-16 method. Future research is expected to develop or test the model with a larger dataset, explore other transfer learning methods, or other conservation areas in Indonesia and beyond to achieve better and more sustainable governance.

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