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## Comparison Accuracy of CNN and VGG16 in Forest Fire Identification: A Case Study

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### ABSTRACT

The current research aims to assess the precision of forest fire detection using CNN and VGG16 models, specifically in the context of fire identification. While both models have demonstrated significant promise in visual pattern recognition, a comprehensive analysis regarding their specific benefits in forest fire identification is still needed. The rationale behind this research stems from the significance of promptly identifying forest fires as a preemptive measure to mitigate their detrimental effects on the environment and society. The employed approach involves the application of transfer learning techniques on a diverse and extensive dataset encompassing different forest fire scenarios. The dataset was used to train both CNN and VGG16 models. The test results indicated that the CNN model achieved a forest fire detection accuracy of 96%, while VGG16 achieved 98% accuracy. The primary objective of this research is to enhance comprehension regarding the merits and demerits of each model in the context of forest fire identification scenarios. While VGG16 exhibits marginally superior performance in identifying forest fires, this discrepancy offers valuable insight into the practical applicability of these two models for fire detection in real-world scenarios. These findings establish a solid basis for the advancement of more dependable and efficient early detection technology in the prevention and management of forest fires in the future. This can be accomplished by capitalizing on the unique capabilities of each model to optimize their performance in practical scenarios.

**Keywords:** CNN; VGG16; Forest Fire Detection; Transfer Learning; Visual Pattern Recognition

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### INTRODUCTION

Wildfires pose a significant risk to both ecosystems and human well-being. The consequences are extensive, as it destroys natural habitats for wildlife, decreases the availability of oxygen, and poses a threat to infrastructure and human well-being. Prompt identification of forest fires is crucial in mitigating the resultant harm. Deep learning technologies, specifically Convolutional Neural Networks (CNN) (Jha & Babiceanu, 2023), (Hindarto & Amalia, 2023) and VGG16, have emerged as promising solutions to enhance early detection. Both models employ artificial intelligence to identify visual patterns, specifically patterns associated with forest fires. The CNN model has demonstrated its efficacy in accurately identifying forest fires by utilizing its capacity to extract features from images.

On the other hand, VGG16 (Hindarto & Afarini, 2023), (Hindarto, 2023b) due to its intricate and complex structure, has a higher capacity to comprehend intricate aspects of images, potentially enhancing the precision of fire detection. However, it is still necessary to conduct a comprehensive assessment of the performance of these two models in the specific context of identifying forest fires. To effectively apply these models in real scenarios, it is crucial to have a thorough comprehension of the benefits and drawbacks associated with each of them, considering the critical importance of early fire detection. The primary aim of this study is to enhance comprehension regarding the potential of these two models in detecting forest fires at an early stage. Additionally, the research seeks to explore methods for optimizing these models to enhance response time and accuracy in mitigating this environmental catastrophe.

While the Convolutional Neural Network (Alzu & Alsmadi, 2022) and the VGG16 architecture (Hindarto, 2023d) have shown impressive abilities in recognizing visual patterns and analysing image data, more extensive research is still needed to compare their strengths and weaknesses, specifically in the context of forest fire identification. The existence of these two models in the field of image recognition has sparked inquiries regarding their comparative efficacy in detecting forest fires, as well as the practical applicability of their limitations and advantages in early detection situations in real-world settings. Although CNNs have demonstrated effectiveness in accurately extracting features from images, the VGG16 architecture, with its increased depth and complexity, offers the potential for a more

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comprehensive comprehension of pictures. This heightened understanding may lead to improved accuracy in identifying forest fires. Nevertheless, it is crucial to gain a more profound comprehension of the performance of both methods in identifying bushfires, given the vital role of early detection in effectively reducing risks. To optimize the practical implementation of these two models on a larger scale, it is crucial to have access to more comprehensive information about their advantages, limitations, and relative performance under different forest fire conditions and contexts. Hence, the objective of this study is to address this deficiency and offer a comprehensive analysis of the reliability of CNN (Hindarto, 2023c) and VGG16 (Sun et al., 2024) as early detection mechanisms for forest fires. Additionally, it aims to explore the adaptability and optimization of these tools for practical implementation in the field, with the goal of mitigating the devastating consequences of forest fires.



Figure 1. Forest fires in Indonesia

Source: Google Image

Frequent forest fires in Indonesia, which have catastrophic consequences, are illustrated in Figure 1. Frequently, forest fires in Indonesia are caused by both natural and human factors, including lightning and dry weather, as well as the uncontrolled burning of agricultural land to clear land. Severe winds and arid weather conditions further complicated the situation, rendering it challenging to contain the fires. The smoke haze that envelops vast areas further detrimentally affects public health as well as the environment and biodiversity, which are all adversely affected by these forest fires. Preventive measures and emergency management, such as vigilant oversight, dissemination of knowledge regarding sustainable agricultural practices, and prompt and effective fire suppression operations, are imperative in surmounting this issue.

In the area of forest fire detection, the prevailing approach was predominantly based on conventional methods that primarily relied on the utilization of sensors and basic algorithms to identify smoke or temperature fluctuations indicative of a fire. While this approach does offer some preliminary information, there is room for improvement in terms of the accuracy and speed of response, often leading to high failure rates or delays in promptly detecting fires. Nevertheless, the advent of artificial intelligence and image processing is causing substantial changes in the way fire detection is approached. The VGG16 architecture and Convolutional Neural Network (Hindarto, 2023a), (Hindarto et al., 2023) are examples of deep learning models that offer a promising approach to comprehending and analysing intricate visual data. CNN, known for its capacity to discern patterns and characteristics from images, and VGG16, renowned for its intricate hierarchical depiction obtained from deep layers, offer advanced solutions for the timely identification of forest fires. These advancements not only enhance the precision of fire detection but also expedite the response to such occurrences. This technology enables a transition from conventional methods with limited capabilities to more advanced and intelligent deep-learning models, offering new possibilities for enhancing the early detection of forest fires. This facilitates the implementation of more dependable, responsive, and efficient detection

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systems that can substantially mitigate the environmental and societal consequences of forest fires. Consequently, advancements in deep learning and image processing technology have led to more inventive and efficient methods in forest fire detection, revolutionizing the field.

The purpose of this study is to compare the VGG16 architecture to the CNN for forest fire detection. This research methodology is predicated on the application of transfer learning techniques to a vast and diverse dataset to uncover information regarding the pros and cons of each model in forest fire detection scenarios. This study aims to explain how both deep learning models process forest fire visual data. By employing transfer learning methodologies, this study aims to assess the degree to which both models can incorporate insights acquired from extensive datasets to identify and classify patterns associated with forest fires. Beyond a mere comparison of accuracy, this study seeks to elucidate specific facets of their performance, including but not limited to sensitivity to environmental fluctuations, capability of identifying fires of varying sizes, and mitigation of identification errors. To achieve this goal, the research endeavours to provide a thorough understanding of the dependability of these two models in real-world scenarios involving forest fire detection. Additionally, it seeks to shed light on potential enhancements or synergies that could be implemented to generate a detection system that is more dependable and adaptable, thereby facilitating the mitigation of forest fire consequences.

### LITERATURE REVIEW

Forest fires not only cause significant environmental damage but also engender profound social and economic repercussions. Impediments to public health, depletion of natural resources, and agricultural output all contribute to substantial economic losses. The present literature review highlights the intricate nature of the forest fire issue in Indonesia. It emphasizes the criticality of preventative measures and comprehensive management to surmount this challenge. The literature review primarily examines the application of CNN and VGG16 detection in object detection, with no explicit mention of forest fires.

Utilizing a refined DenseNet backbone, a soft attention mechanism, and a mono-depth and atmospheric scattering model, this study proposes an extensive data augmentation strategy for early fire detection. The model outperforms current state-of-the-art models in terms of accuracy when applied to both original and augmented datasets. Furthermore, it exhibits exceptional performance and resource efficiency, rendering it well-suited for deployment in real-time on-edge devices. Model accuracy of 96.40% to 98.47% (Yar, Ullah, et al., 2023). Humans and the environment are devastated by fires. Recent studies suggest using computer vision to create a low-cost fire detection system. The paper introduces a transfer learning framework for fire detection using CNNs trained on real-world fire images. Additionally, the framework employs Grad-CAM to visualize and locate fire in images. The attention mechanism in the model has helped the network perform better. The Grad-CAM results showed that attention improved fire localization in images. After examining many models, EfficientNetB0 was the best fit. A test accuracy of 95.40% validates the model's fire detection efficiency in the selected real-world fire image dataset. The network's high recall of 97.61 indicates low false negatives, making it reliable for fire detection (Majid et al., 2022). Fires cause deaths, economic and ecological chaos, property damage, and climate change—critical early detection with vision sensors. A modified YOLOv5s model with a Stem module, smaller kernels, and a P6 module detects small and large fire regions with a reduced complexity and size (Yar, Ahmad, et al., 2023). This paper uses attention mechanisms and feature-level and decision-level fusion modules to detect smoke in average and foggy weather. A new fog smoke dataset, attention mechanism module, and lightweight feature-level and decision-level fusion module are used. Studies show that the method outperforms other methods in slight smoke and complex negative sample detection in accuracy, precision, recall rate, and F1 score (He et al., 2021). This research monitors and detects construction machinery to optimize site operations. Image classification algorithms can detect construction machinery, but drone images may be inefficient for larger areas. Satellite image classification detects construction machinery, and convolutional neural network architectures are evaluated. The best models for illegal aggregate mining detection are DenseNet161 and ResNet101, with 91,9% and 90,3% test accuracies (Yeşilmen & Tatar, 2022).

Fire detection using vision computing technology is studied using DenseNet augmentation, YOLOv5s, smoke, and fire detection. Integrating multi-sensor data, improving detection accuracy, and adapting the model to different environments require more research.

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**METHOD**

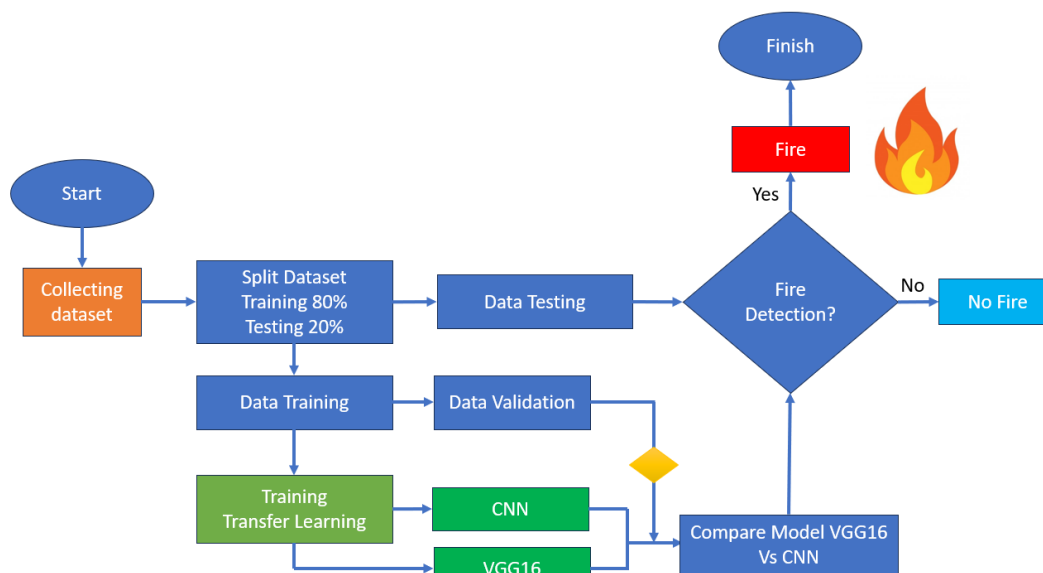


Figure 2. Proposed Research Method  
Source: Researcher property

Figure 2 illustrates the research methods employed in this study, starting with the collection of the dataset. This step is essential in the development of a fire detection model. The dataset utilized should be inclusive and varied, encompassing images that feature fire as well as those that do not (No Fire) from a multitude of sources and conditions. Once the dataset has been gathered, the subsequent step involves partitioning the data into two primary components: the training data and the testing data. The division is conducted using an 80% proportion for training data, which will be utilized to train the model, and a 20% proportion for testing data, which will be employed to evaluate the performance of the trained model. Next, we will apply transfer learning techniques utilizing a Convolutional Neural Network (CNN) and the VGG16 architecture. Transfer learning allows for the utilization of knowledge acquired by previous models on comparable tasks, thus enhancing the speed and efficacy of the fire detection model under development. In this scenario, retraining is performed on specific components of the previously trained model, utilizing a prearranged dataset. Following the completion of the training process utilizing transfer learning on both model architectures, testing is conducted using pre-separated testing data. The purpose of this test is to assess the efficacy and precision of the model in identifying the existence or non-existence of fire in previously unseen images that were not used for training.

The test results were used to compare the performance metrics, including accuracy, precision, recall, and F1-score, of the CNN model and the VGG16 model. This analysis facilitates comprehension of the merits and drawbacks of each model in the realm of fire detection. Models that exhibit superior performance in categorizing images as either fire or non-fire are deemed more effective and thus may be a more favorable option for practical application. This research holds substantial significance within the realm of security and the timely detection of fires. By employing this research methodology, we aim to develop a dependable and precise model for identifying fires in novel images. This model can then be implemented in real-time fire detection systems to mitigate losses resulting from fires.

### Convolutional Neural Network

To detect forest fires from image data, a Convolutional Neural Network (Cinyol et al., 2023), (Duarte et al., 2023) is a highly effective technology. This technology enables the system to autonomously acquire significant characteristics from the images utilized during the training procedure. CNN employs multiple layers to process pictures sequentially. The layers comprise convolution layers, pooling layers, and fully connected layers. Convolution layers are responsible for extracting crucial features from images. As a Convolutional Neural Network trained to detect forest fires, this layer will acquire the ability to recognize specific characteristics associated with the existence of fire,

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including attributes like color, texture, and visual patterns commonly found in fire-related images. The pooling layer is used to make the features extracted by the convolution layer more concise. This facilitates the preservation of crucial data while simultaneously reducing computational intricacy. Pooling techniques, like max pooling, preserve the essential characteristics of each section of the convolved image, thereby reducing the number of parameters needed during training.

The fully connected layer is the concluding component of the CNN, responsible for amalgamating the extracted features and establishing connections with layers of neurons to execute the ultimate classification, explicitly determining whether the image includes fire or not. The efficacy of CNN in detecting forest fires is significantly contingent upon the caliber and portrayal of the dataset employed during the training process. An optimal dataset should encompass both fire and non-fire images sourced from diverse origins, encompassing a range of lighting conditions and shooting perspectives. A diverse dataset enhances CNN's ability to discern patterns associated with forest fires.

In addition, transfer learning plays a crucial role in the development of CNN models for forest fire detection. This technique exploits the knowledge acquired by pre-existing models on analogous tasks. Transfer learning allows CNN models to utilize previously acquired knowledge from larger datasets or similar tasks, resulting in enhanced performance and accelerated development of fire detection models. A proficiently trained Convolutional Neural Network model can be effectively utilized in real-time forest fire detection systems. The system can rapidly analyze images captured by cameras or satellite imagery to promptly detect and issue an early warning in the event of a fire. This enables a more expedient response in managing forest fires and can aid in endeavors to mitigate further devastation.

## VGG16

The efficacy of the VGG16 Convolutional Neural Network architecture (Kumar & Kumar, 2023), (Sharma et al., 2022) in a range of image recognition applications, such as forest fire detection, has been demonstrated. Sixteen layers comprised of convolution layers and intense, fully connected layers comprise VGG16, which the Visual Graphics Group developed at the University of Oxford. The VGG16 framework is distinguished by its exceptionally symmetrical configuration, and the utilization of deep convolutional layers that employ small (3x3) filters iteratively. By doing so, VGG16 can acquire extremely detailed and hierarchical representations of the training images. The extraction of critical image features is the function of the convolution layer in VGG16. From the initial layer to the last, this procedure is executed in stages. The capture of visual patterns by each convolutional layer encompasses a spectrum of complexity levels. These patterns extend from essential elements like lines and angles to more abstract characteristics like textures and patterns associated with forest fires. In addition, VGG16 incorporates a max pooling layer that accomplishes the practical task of reducing the size of the extracted features. By aggregating the maximum value from every region of the convolution output, max pooling aids in the preservation of critical data while decreasing computational complexity. A fully connected layer completes VGG16 by establishing connections between the extracted features and the neuron layers responsible for carrying out the ultimate classification. The model acquires the ability to distinguish between images that depict forest fires and those that do not. One of the primary strengths of VGG16 is its capability to acquire highly detailed representations from images. However, its large number of parameters necessitates more intensive computing and a more extensive training dataset. To detect forest fires, transfer learning may also be implemented on the VGG16 architecture. The VGG16 model can effectively utilize transfer learning to apply insights gained by preceding models during comparable tasks. This may enhance the fire detection performance of the model, particularly in situations where the training dataset is constrained. The practical implementation of a properly trained VGG16 in a real-time forest fire detection system utilizing satellite or camera imagery is possible. By facilitating a quicker response to forest fires and providing early warnings, this model has the potential to mitigate the financial losses associated with such incidents.

## RESULT

### Dataset Fire and No Fire Forest

The Kaggle-accessible forest fire dataset is a crucial resource for the development of fire detection models. This dataset, comprising 755 image data for the training phase and 244 image data for testing, offers a reasonably comprehensive depiction of diverse forest fire circumstances and occurrences. In training the model to distinguish visual distinctions between fire and other backgrounds and to identify patterns associated with the presence of fire, each image in this dataset contributes significantly. The 755 images comprising the model's training data offer

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considerable diversity, enabling it to acquire knowledge from an array of situations, including but not limited to various fire intensities, fire sources, weather conditions, and environmental circumstances. In the interim, 244 images of testing data present an opportunity to evaluate the trained model's ability to generalize its knowledge to never-before-seen data. Critical information regarding the performance of the model in identifying forest fires across various environments will be obtained through the testing procedure conducted on this dataset.

Using this dataset does, nevertheless, necessitate a thorough evaluation of the data's quality and the suitability of the representation of forest fires. A high-quality dataset is a crucial prerequisite for the model's success in identifying fire-related patterns. Hence, when choosing this dataset, critical considerations included the representativeness of different fire conditions, including fire scale, burned vegetation type, viewpoint, and other environmental factors. Subsequently, rigorous testing must be performed on 244 test image datasets in order to determine the model's dependability in handling conditions that may have yet to be encountered before and its ability to distinguish forest fires accurately. Therefore, for the development of a fire detection model, the forest fire dataset obtained from Kaggle, which comprises 755 training data and 244 testing data, serves as a solid foundation. It is critical to ensure the model's reliability and generalizability in real-world applications by conducting a thorough evaluation of the model's performance in identifying fires on never-before-seen data and by considering the diversity and appropriate representation of fire conditions in the dataset during the model development process. The dataset can be seen in Figure 3.



Figure 3. Dataset  
Source: Dataset Kaggle

### Convolutional Neural Network

The outcomes of the model are depicted in Figure 4A. Summary () function of the Convolutional Neural Network (CNN) architecture that was developed. The framework of the CNN is thoroughly described in the model. Summary () function, which includes the number of layers, layer types (e.g., Convolutional, Pooling, and Fully Connected), and the number of parameters utilized in each layer. This data is essential for comprehending the model's complexity, the required number of weights, and the way visual information traverses the network.

The graphs in Sections B and C illustrate the model training procedure, encompassing key performance indicators such as validation loss, train loss, and validation loss. As the training process advances, the train accuracy and validation accuracy graphs demonstrate how well the CNN model can classify training and validation data. A graph exhibiting superior performance will approach 1. In the interim, the model's accuracy in estimating the actual values is demonstrated through the train loss and validation loss graphs. The model gains more knowledge and optimizes its predictions as the loss line decreases.

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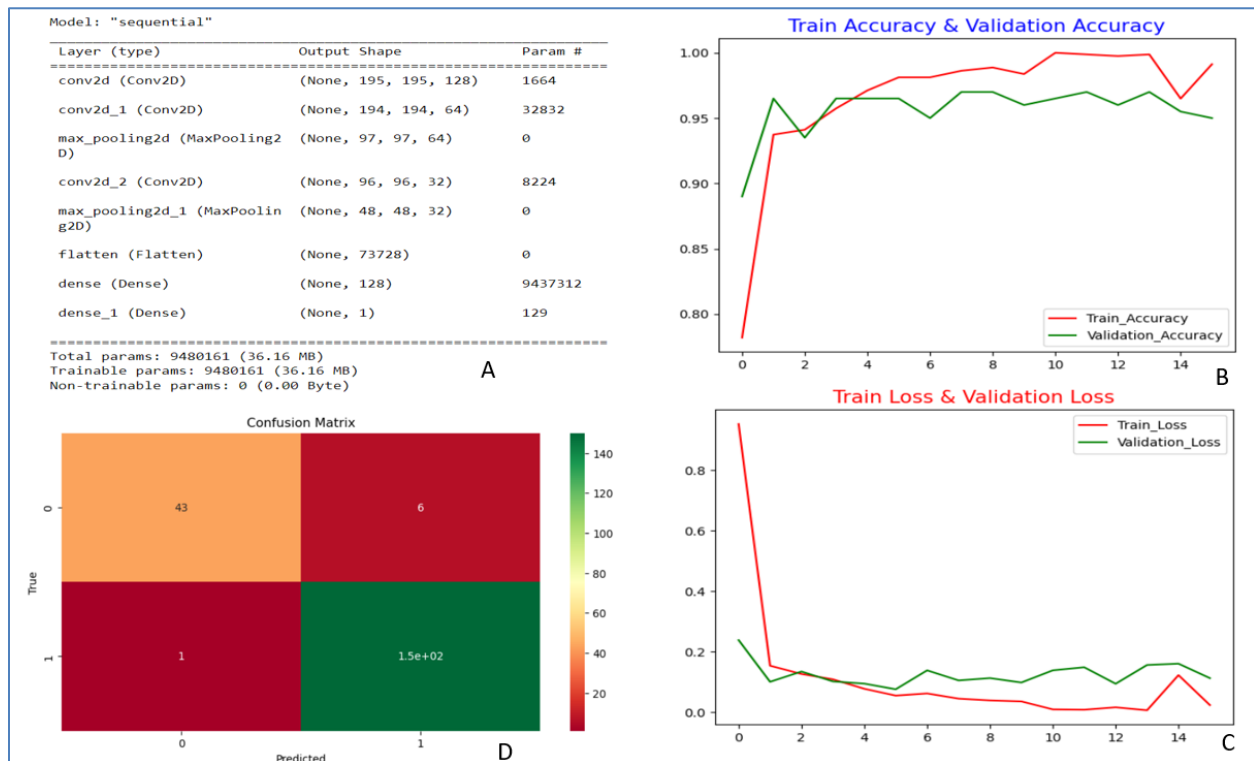


Figure 4. Results of training experiments using Convolutional Neural Network  
 Source: Researcher property

The confusion matrix, located in part D, is subsequently employed to assess the performance of the model on the test data. In evaluating the performance of a model in classifying data into distinct categories, a confusion matrix is a tabular representation. The confusion matrix can be utilized to categorize forest fire detection incidents into the following states: correctly identified fires (true positives), undetected fires (false negatives), inaccurately identified fires (false positives), and undetected fires (true negatives). A multitude of evaluation metrics, including precision, recall, and F1-score, can be derived from this confusion matrix. These metrics offer a more comprehensive assessment of the model's effectiveness and dependability in forest fire detection.

A comprehensive understanding of the CNN model's performance and complexity in forest fire detection can be obtained by integrating data from the confusion matrix, train/validation accuracy and loss graphs, and model. Summary (). This analysis is crucial for determining the model's generalizability and ability to learn from training data, in addition to assessing the model's accuracy and dependability in classifying images of forest fires. Researchers can enhance the performance of forest fire detection by refining models, adjusting parameters, or identifying areas that require improvement after gaining a comprehensive understanding of these results.

### VGG16

The outcomes of the model are depicted in Figure 5A, the summary() function is utilized to depict the architecture of the VGG16 model, which is a Convolutional Neural Network (CNN) renowned for its intricate nature. Convolution, pooling, and fully connected layers comprise the 16-layer deep structure of the VGG16 architecture, which enables it to learn complex image features—the data illustrated by the model. The parameter summary() offers an exhaustive depiction of the parameters and layer composition utilized in this architecture.

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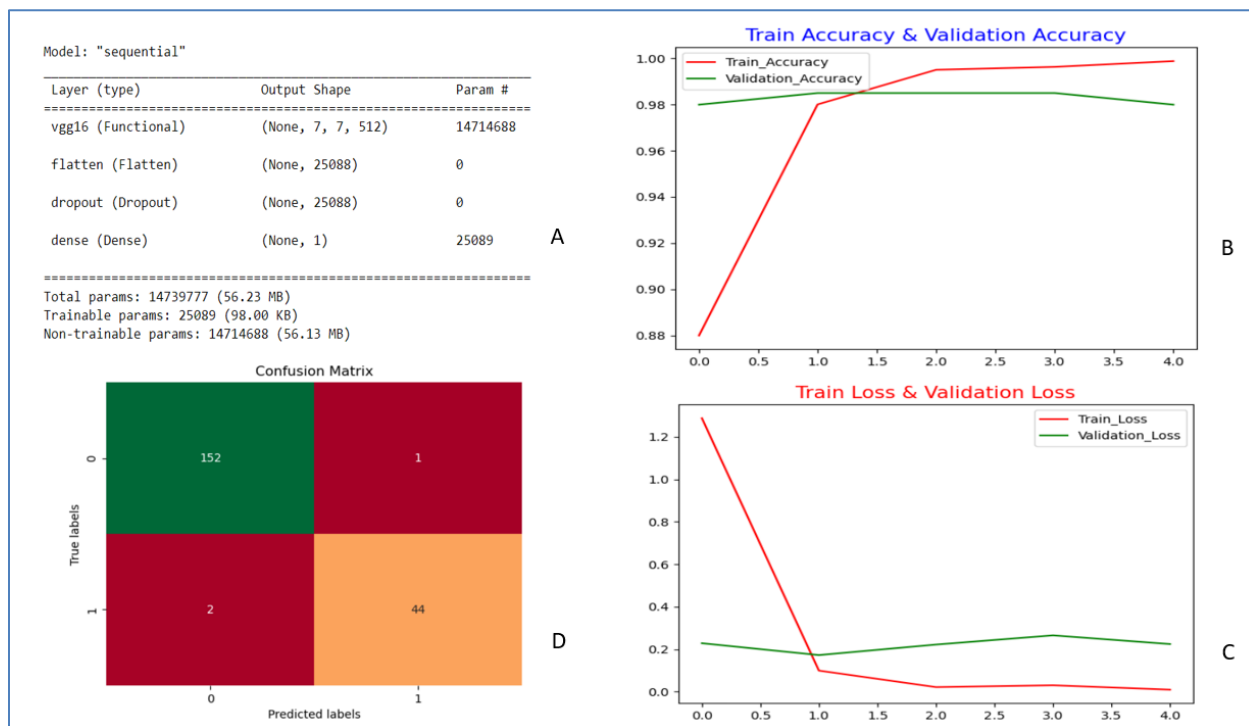


Figure 5. Results of training experiments using VGG16

Source: Researcher property

The training process of the VGG16 model is represented graphically in Parts B and C, which contain data on training loss, validation loss, training accuracy, and validation loss. The accuracy graphs for training and validation illustrate the degree to which the model correctly classifies training and validation data throughout the training phase. The VGG16 model exhibits a notable capacity for accurately identifying patterns associated with forest fires, as evidenced by its attainment of 98% accuracy. In contrast, the accuracy of the model's estimation of the valid values is demonstrated by the training loss and validation loss graphs. The model's ability to learn and optimize its predictions effectively is shown by the loss value of 0.0094.

Following this, section D contains a confusion matrix that is employed to assess the VGG16 model's performance on the test data. An evaluation of a model's accuracy in categorizing data into different groups can be seen in a confusion matrix, a tabular representation. The confusion matrix is a valuable tool in forest fire detection as it facilitates the assessment of the model's accuracy in distinguishing between fires and non-fires. It accomplishes this by considering true positives, false negatives, false positives, and true negatives. Depicting the accuracy and dependability of the model in identifying forest fires, evaluation metrics, including precision, recall, and F1-score, are computed using the confusion matrix as their foundation.

A thorough comprehension of the VGG16 model's performance and intricacy in forest fire detection can be obtained from the information contained in the confusion matrix, train/validation accuracy, loss graphs, and the overall data obtained from the model summary (). This analysis presents a comprehensive evaluation of the model's performance in classifying forest fire images, including its ability to learn from training data and generalize to test data, as well as its accuracy and dependability. Researchers can formulate strategies to enhance the performance of the VGG16 model in detecting forest fires and adjust or improvements to the model with a thorough understanding of these results.

**Performance**

Table 1 displays the evaluation metrics for finding forest fires; Convolutional Neural Networks are used. To find out how well the model distinguishes between fire and non-fire images, we use these metrics. With a precision of 0.98 for class 0 (non-fire) and 0.96 for class 1 (fire), we can see that the model is very accurate in identifying the class, and

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it also shows how many of the positive results it produces are relevant. The number of relevant events that the model can detect is measured by recall, which is also called sensitivity. Class 0's recall of 0.88 and Class 1's recall of 0.99 show that the model can accurately identify fires, with Class 1 having an exceptionally high recall.

The F1-score gives a general view of the model's performance since it is the harmonic average of the recall and precision. Here, we can see that recall and precision are well-balanced, with F1 scores of 0.98 for class 1 and 0.92 for class 0. To add to that, the number of examples utilized in each class for evaluation purposes is supported. The model's overall classification accuracy on 200 samples is demonstrated by the accuracy result (accuracy) of 0.96. Globally, evaluation metrics like macro average and weighted average paint a picture of how well the model is doing by averaging each metric across all classes. Based on this evaluation, the CNN model performs well in detecting forest fires, with a satisfactory level of accuracy and fire detection ability, as evidenced by a macro average value of 0.97 and a weighted average of 0.96.

Table 1. Evaluation Metrics Convolutional Neural Network  
Source: Researcher Property

|              | Precision | Recall | F1-Score | Support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.98      | 0.88   | 0.92     | 49      |
| 1            | 0.96      | 0.99   | 0.98     | 151     |
| accuracy     |           |        | 0.96     | 200     |
| macro avg    | 0.97      | 0.94   | 0.95     | 200     |
| weighted avg | 0.97      | 0.96   | 0.96     | 200     |

A variety of metrics for assessing the VGG16 model's performance in detecting forest fires are presented in Table 2. These metrics give a general idea of how well the model did at identifying fires from photos. With a precision of 0.99 for class 0 (non-fire) and 0.98 for class 1 (fire), the model clearly can produce accurate prediction results. Precision is a measure of how well the model anticipates positive outcomes. The number of relevant events that the model is able to detect is called recall or sensitivity. The model's excellent fire detection capabilities and excellent non-fire identification abilities are demonstrated by the recall results of 0.99 for class 0 and 0.96 for class 1. An aggregate measure of a model's efficacy, the F1-score is the harmonic mean of its recall and precision. With an F1-score of 0.99 for class 0 and 0.97 for class 1, it is clear that there is a decent compromise between recall and precision when classifying the two groups. How many samples were used in each class for the evaluation is called support. When it comes to categorizing 199 samples, the model's accuracy of 0.98 really shines. In order to get a global view of the model's performance, evaluation metrics like macro average and weighted average average each metric across classes. Given that the VGG16 model demonstrates a weighted average of 0.98 and a macro average of 0.98, it is evident that it performs exceptionally well in detecting forest fires. It proves remarkable accuracy and strong capability in classifying both types of data.

Table 2. Evaluation VGG16

|              | Precision | Recall | F1-Score | Support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.99      | 0.99   | 0.99     | 153     |
| 1            | 0.98      | 0.96   | 0.97     | 46      |
| accuracy     |           |        | 0.98     | 199     |
| macro avg    | 0.98      | 0.97   | 0.98     | 199     |
| weighted avg | 0.98      | 0.98   | 0.98     | 199     |

## DISCUSSIONS

How to make fire detection using the CNN and VGG16 algorithms to detect forest fires? (RQ 1)

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Visual identification of forest fires is accomplished effectively using the Convolutional Neural Network algorithm and VGG16. CNN processes image data in a manner analogous to how the human brain interprets visual information; it is a type of machine learning algorithm. With sixteen layers, the VGG16 is a well-known CNN architecture capable of learning complex image features. Gathering a dataset comprising both forest fire and standard landscape images is a crucial initial stage in the development of a forest fire detection system utilizing CNN and VGG16. For the model to distinguish visually between forest fires and normal conditions, this data set serves as the learning foundation. Subsequently, to train and evaluate the model, this dataset is partitioned into two subsets: training and validation. The model layers are subsequently incrementally learned utilizing the training data and the VGG16 architecture. To analyze patterns associated with forest fires, this procedure entails the extraction of features from images of a dataset. VGG16 can identify patterns that correspond to forest fires due to the progressive comprehension of progressively intricate image features by its layers. CNN and VGG16 models can be employed to identify forest fires in novel images once the training procedure is fully executed. The model will generate predictions on the basis of prior learning after images are input into it during this procedure. Indicating the presence of a forest fire, the model will generate output once it has identified patterns in newly acquired images that are indicative of fires. Notably, both the quality of the training dataset and the parameters adjusted during the learning process have a substantial impact on the effectiveness of forest fire detection with CNN and VGG16. Furthermore, consistent modeling and testing are imperative to ascertain that the model retains its ability to detect forest fires across diverse visual circumstances accurately. The forest fire detection system has the potential to become an efficient instrument for averting and promptly addressing forest fires that pose a threat to both security and the environment by integrating the capabilities of CNN and the VGG16 architecture. Experimental studies and descriptions of the process can be found in research methods.

Does it facilitate the development of more effective preventive measures and produce more precise prediction models for early fire pattern identification? (RQ 2).

It is critical for the success of forest fire prevention initiatives to develop prediction models that pinpoint early patterns with greater precision. Prevention measures can significantly mitigate the detrimental effects of forest fires on both assets and the environment. This can be accomplished in part by constructing more sophisticated prediction models using cutting-edge technologies, such as data analysis and machine learning. There are instances where early indications of forest fires may lack discernible visual characteristics. On the contrary, early indications of a fire can be discerned by models trained to recognize subtle patterns via the implementation of machine learning methods, including Convolutional Neural Network (CNN)-based algorithms. Convolutional neural networks (CNNs) enable the model to acquire knowledge and discern distinct visual characteristics present in fire images as well as those of a typical forest setting, including smoke patterns, elevated brightness, and color alterations.

A representative dataset that encompasses a range of fire conditions, as well as typical forest conditions, is essential for constructing a more precise prediction model. Weather conditions, topographical features, vegetation types, and fire intensity must all be represented in a balanced dataset. By virtue of the model gaining knowledge and differentiating attributes that are unique to the initial fire conditions through training with such a dataset, earlier identification is made possible. Furthermore, model accuracy is enhanced through the incorporation of advanced sensor technology into forest fire monitoring. Supplementary data to the visual information acquired by the model can be obtained through the utilization of technologies such as temperature sensors, humidity sensors, and satellite imagery. Enhancing the dependability of prediction outcomes, data from these sensors may be employed to validate patterns identified by prediction models.

Accurate prediction models can expedite the response to detected fires in the context of more effective preventative measures. The implementation of an early detection system for fires enables prompt implementation of preventative measures, including but not limited to resource allocation to mitigate fire propagation, early notification to authorities, and mobilization of firefighting units. Implementing a prompt reaction can effectively reduce the extent of the fire, safeguard endangered plant and animal life, and restrict ecological harm. Practical prevention efforts require, in conclusion, the development of more precise prediction models that can identify early patterns of forest fires. A foundation for the development of more sophisticated prediction models is a fusion of machine learning technology, representative datasets, and sensor technology integration. Destroying forest fires can cause significant damage to forest ecosystems and result in substantial losses; therefore, a dependable early fire detection system can significantly contribute to these objectives.

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## CONCLUSION

The Kaggle-accessible forest fire dataset is a valuable resource for developing fire detection models. It contains 755 image data for training and 244 images for testing, providing a comprehensive depiction of diverse forest fire circumstances. The model's performance in identifying forest fires across various environments is evaluated through rigorous testing on the dataset. The Convolutional Neural Network (CNN) architecture is developed, with graphs illustrating the model's training procedure and performance indicators. The confusion matrix categorizes forest fire detection incidents into correctly identified, undetected, inaccurately identified, and undetected fires. The VGG16 model, renowned for its intricate nature, is used for its training process. The model achieves 98% accuracy in identifying patterns associated with forest fires, while its accuracy in estimating valid values is demonstrated by training loss and validation loss graphs. The VGG16 model is evaluated for its performance in forest fire detection using a confusion matrix. The accuracy of the model's data classification is assessed by utilizing this matrix, which considers true negatives, false positives, and false positives. Evaluation metrics such as precision, recall, and F1-score are computed using the confusion matrix. The model's performance is evaluated on 200 samples, with an accuracy of 0.98 for class 0 (non-fire) and 0.96 for class 1 (fire). The F1 score measures the harmonic average of recall and precision, with F1 scores of 0.98 for class 1 and 0.92 for class 0. The model's overall classification accuracy on 200 samples is 0.96. The model's performance is analyzed globally using macro and weighted average metrics, demonstrating remarkable accuracy and strong capability in classifying forest fires.

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