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FOREST FIRE DETECTION USING TRANSFER LEARNING MODEL WITH CONTRAST ENHANCEMENT AND DATA AUGMENTATION

Vina Ayumi[1], Handrie Noprisson[2], Nur Ani[3]

[1,2] Department of Informatics, Faculty of Engineering and Informatics, Universitas Dian Nusantara
[3]Institute of Visual Informatics, Universiti Kebangsaan Malaysia

email: vina.ayumi@dosen.undira.ac.id [1], handrie.noprisson@dosen.undira.ac.id[2], p93828@siswa.ukm.edu.my[3]

Abstract

Forest damage due to fire is unique of the catastrophes that can disrupt and damage the existing ecosystem. There needs to be a quick response to fires because disaster management takes longer, and the impact of the damage will be more severe. To process images to detect fire in the forest, we need to build a suitable deep-learning model. This study proposed research on forest fire detection using an Xception and MobileNet model. Moreover, this research optimizes the accuracy of the model by applying Contrast Limited Adaptive Histogram Equalization (CLAHE) and data augmentation to tackle the problem of the forest fire image dataset. Based on the experiment, MobileNet with CLAHE obtained 99,66% accuracy in the test phase. In the same phase, MobileNet with CLAHE obtained a value F1-score of 1.00, a value of precision of 0.99, and a value of recall of 1.00. If compared to other model performances, MobileNet with CLAHE obtained the best result.

Keywords: CLAHE, MobileNet, Xception, forest fire detection, deep learning, computer vision

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INTRODUCTION

Natural damage from fires is usually in remote areas far from human control. Dry wood and dry leaves encourage the firing process to accelerate if a fire is burning. The ignition of a fire can happen by several factors, for example, sunlight reflecting off the broken glass or a fire that appears due to human activities (such as smoking or other) [1]–[3].

Forest damage due to fire is solitary of the ruins that can disrupt and damage the existing environment. There needs to be a quick response to fires because disaster management takes longer, and the impact of the damage is more severe. Early warning of a fire disaster can be a solution to provide information quickly about the location and level of fires [4]–[6].

Currently, video cameras have been developed that can be used to take pictures at specific locations. It can be combined with machine learning and image processing technology. In that case, the image can be processed into information used to develop an early warning system for a fire disaster. With this system, it is hoped that it make it easier to detect fires automatically at a low cost [7]–[9].

To process images to detect fire in the forest, we need to build a suitable deep-learning model. Several researchers have been evaluating the performance of neural network algorithms for forest fire recognition. For example, Suwansrikham et al (2023) explore transfer learning on pre-trained models, including ResNet and Inception. As the result of research, ResNet-26 ResNet-50, Inception-v3, and Inception-v4 respectively obtained accuracies of 86,66%, 85,64%, 83,25%, and 80,86% [10]. Then, Xie & Huang (2023) also projected a technique for forest fire recognition using improved transfer learning. This research used the Faster RCNN algorithm and achieved a detection accuracy of 93,70% in fire forest images [11]. Moreover, Luo et al., (2023) researched forest fire detection using neural network with transfer learning. This research used the Densenet-201 model and obtained 98,46% accuracy. [12].

However, the previous research has not explored all of the transfer learning methods yet, including MobileNet and Xception. This research explores both algorithms to identify model performance for fire forest detection. Moreover, MobileNet has several advantages for fire detection than Xception. MobileNet remains a lightweight transfer learning model that reduces the parameter size and increases speed, making it well-suited for edge computing environments with limited storage and energy

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consumption. Additionally, MobileNetV2, a variant of MobileNet, achieves high accuracy for fire detection while using fewer parameters compared to other networks [13]–[15].

The other case of fire forest detection is related to the quality of the dataset. Forest fire datasets have several contrast issues. Contrast enhancement techniques have been applied to forest fire datasets to improve the visibility and clarity of the images. One method proposed is the use of a digital imaging tool that converts the original color of the image to improve the contrast of the image namely Contrast Limited Adaptive Histogram Equalization (CLAHE) [16]. CLAHE remains a method used for image quality improvement. CLAHE is effective in enhancing the contrast of images while avoiding over-amplification of noise. It has been shown to improve the eminence of images in low-light conditions. The method achieves this by performing histogram equalization on the image, which improves the brightness and contrast of the image [17], [18].

Based on the above background, this study proposed research on forest fire detection using an Xception and MobileNet model. Moreover, this research optimizes the accuracy of the model by applying CLAHE to tackle the problem of forest fire image quality.

METHOD

This research explored the Xception and the MobileNet model for fire detection. Then, this research also examined the method of CLAHE to solve the contrast problem of forest fire images before image dataset processed by MobileNet. To achieve the research aim, this research phase is elaborated into several phases as depicted in Figure 1.

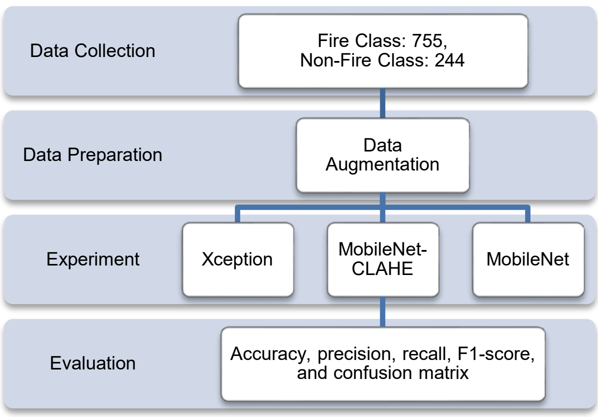
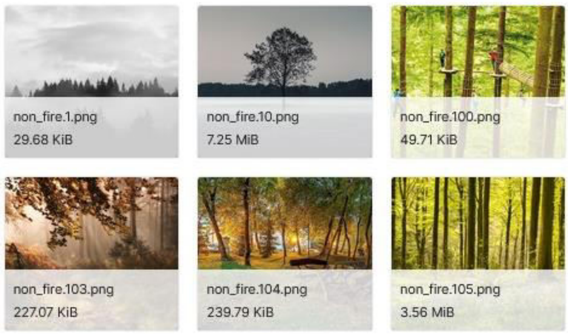


Figure 1. Research Methodology

The first phase is data collection. The data is collected from several sources on the internet [19]–[22]. The dataset consists of 2 classes: fire (images that contain fire) and non-fire (regular images that do not have fire). The fire class contains 755 pictures of outdoor fires, some of which contain thick smoke. The non-fire category contains 244 natural images that do not have fire (for example, waterfall, lake, grass, river, people, forest with foggy condition, road, and forest). All images have a random size in jpg format which is depicted in Figure 2.

(a) fire class



(a) non-fire class

Figure 2. Examples of dataset

Then, the data is applied to the technique of augmentation, including rotation, brightness, height shift, horizontal flip, width shift, and vertical flip. The outcome of data augmentation is the new image dataset applied the rescaling factor by multiplying each pixel by 1/255 on all training, validation, and testing data.

The experiment used three types of models, including Xception, MobileNet, and MobileNet with CLAHE. Xception stands for the Extreme version of Inception developed by Google. The model of the Xception is a pointwise convolution followed by a depthwise convolution. The modifications to Xception are the inception layer in Inception-v3, where 1×1 convolution is completed first before any layer of n×n spatial convolutions [23]–[26].

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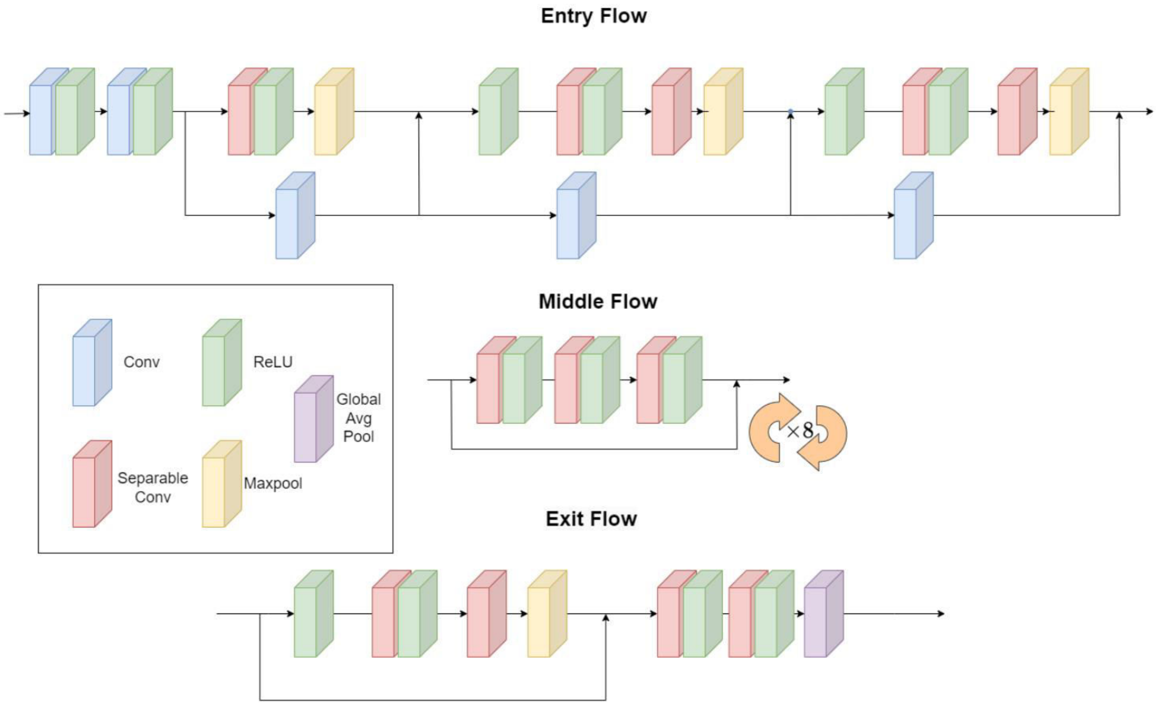

Figure 3. Xception architecture [27]

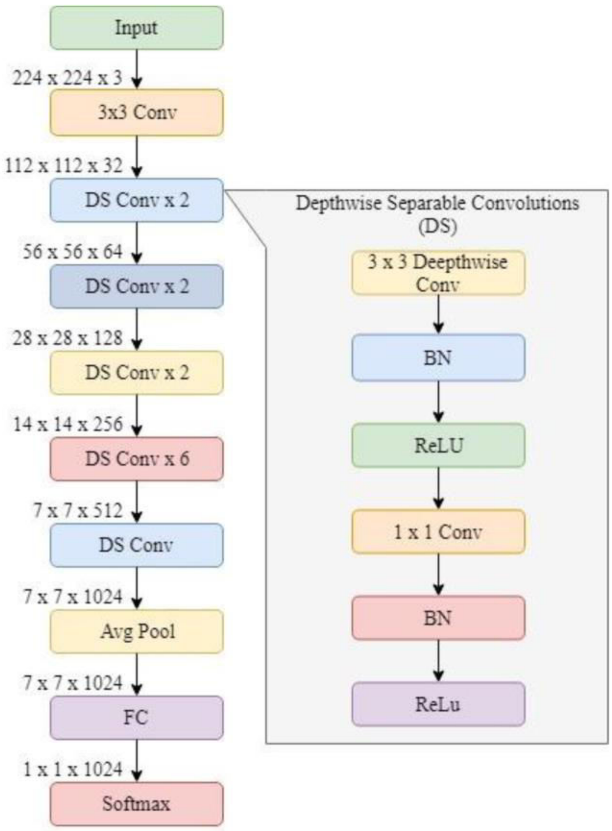

Figure 4. MobileNet architecture [28]

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Then, the experiment used MobileNet and MobileNet with CLAHE. We compared Xception, MobileNet, and MobileNet with CLAHE to obtain the best model for training and validating data. After obtaining the best model in the previous stage, the next step is to predict the testing data with the model generated during the last phase. The final phase is to calculate the evaluation matrix for the testing data, including CM or confusion matrix, ACC or accuracy, PRE or precision, and REC or recall.

RESULT AND DISCUSSION

This research explored the Xception and MobileNet models for fire detection. Then, this research also examined the contrast enhancement and data augmentation method to resolve the problematic of forest fire image.

Data Augmentation

The used dataset was retrieved from several resources and contained two classes: fire (pictures including fire) and non-fire (regular images that do not contain fire). In the fire class, there are 755 data of flames in outdoor, some of which involve thick smoke. The non-fire class with 244 natural photos devoid of fire (for example, grass, waterfall, river, people, and many more).

This research begins with pre-processing the data, which entails partitioning the dataset into training, validation, testing data, and augmenting the dataset's picture with ImageGenerators. The data is then applied to the rotation, width-shift, brightness, height-shift, vertical-flip, and horizontal=flip parameters. In addition, a rescaling factor is added to all training, validation, and testing data by multiplying each pixel by 1./255.

Model Xception

In the first experiment, we used Xception. In the training and data validation stages, the pre-trained layers model is used for training, and Xception is used to validate the data. The Xception has a parameter set, including batch size with value of 32, epoch with value of 20, optimizer with value of Adam, learning rate with value of 0.001, and image size with value of 229 x 229 pixels. To measure the Xception performance, we used CM or confusion matrix, ACC or accuracy, PRE or precision, and REC or recall. The accuracy result of Xception for the train, validate, and test phase is depicted in Figure 5.

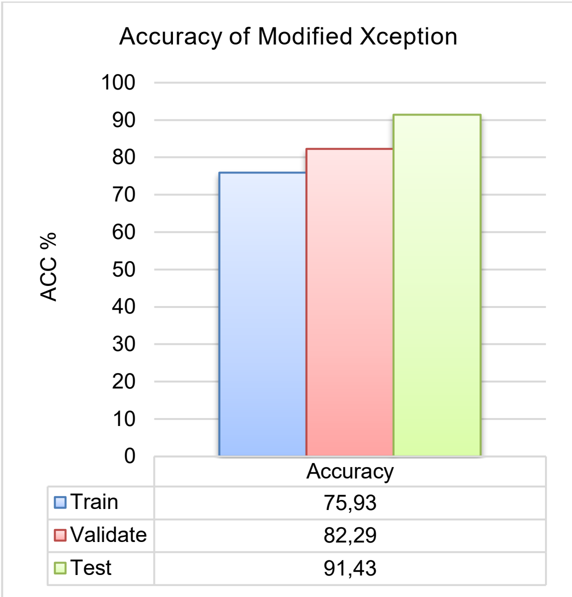

Figure 5. Accuracy of Xception

Based on the experiment, Xception obtained 91,43% accuracy in the test phase. In the same phase, the Xception obtained value of F1-score is 0.91, rate of precision is 0.92, and value of recall is 0.91. The test result of Xception indicates that the accuracy value reached may be satisfactory. In addition to seeing the false or true positive error and the false or true negative error, the experiment is also analyzed using a confusion matrix. The result of confusion matrix of Xception is depicted in Figure 6.

	Fire	Non-Fire
Fire	224	1
Non-Fire	24	43

Figure 6. Confusion Matrix of Xception

The analysis using the confusion matrix results shows that the model can predict almost all fire classes with correct predictions of 224 images from a total of 225 images. Only one image was mispredicted. As for the non-fire class, the model can predict almost 3/4 of the number of images, with a correct prediction of 43 images out of 67 total images.

The basis for Xception, which differs from Inception in that its module is replaced with depthwise layer of separable convolution. In transfer learning architecture, depthwise layer of separable convolution, also known as separable layer of convolution, consists of depthwise convolution, in which spatial layer of convolution is carried out independently on each input channel, followed by pointwise convolution.

For instances, convolution with 1x1, which projected the output channel with a depthwise convolution to the new channel space. The Xception architecture comprises a depth-wise layer of separable convolution and residual layer of connections. The image below shows the prediction results of some 48 random images. In the prediction results from 48 images, only three images were wrongly predicted, namely the non-fire image, which was incorrectly expected to fire.

Figure 7. Xception Correct Prediction Results

The Inception idea is implemented in the Xception model for fire image detection. According to this idea, each convolution layer of a neural network is broken down into a series of operations using cross-channel correlation and spatial correlation. With the utilization of Inception, accuracy can be improved through the utilization of more effective model parameters (correlation).

The Xception Model, used for detecting fires in images, has convolutional layers built into its architecture. These layers comprise the feature extraction based on neural network. The convolutional layer of Xception utilized for detecting fire has been reorganized into several modules. All of the modules excluded by the first modules and last modules, have linear residual connections surrounding them. The suggested model is a linear with stack condition that is comprised of depthwise layer of separable convolution layers' that are outfitted with residual layer of connections.

To obtain information regarding the outcomes of the testing procedure, four distinct data kinds will be utilized as output. These include real negative and positive data, false positive and negative data, and data with false negative. The term data with false positive condition refers to information that the model identifies as "positive data," even when it really ought to be "negative data" (according to a fire or non-fire label, but it should not match). Data that the model identifies as positive and positive are both referred to as true positive data (matches a fire or non-fire label and is a true match). The term "false negative data" refers to information that the model identifies as "negative data," but which is, in fact, "positive data" (detected does not match a fire or non-fire label but should match). Finally, the term "true negative data" refers to information that has been identified as "negative data" by the model, and it is accurate in describing the information as "negative data" (detected does not match a fire or non-fire label and indeed does not match).

Figure 8. Xception Model Incorrect Prediction

The origins of the Xception architecture are to gain a better improvement of this particular framework. Transfer learning is a method that seeks to improve learners in one domain by transferring information from other domains that are similar to the one in which the learners are working. The Xception model, which is used to detect API images, is one such method. If you only have a small amount of data to work with during training, one strategy you could use is transfer learning.

Utilizing a architecture that has already been trained (pre-trained) with large scale of training data and then reusing that model to extract features from new data is an example of architecture of transfer-learning. Transfer learning can generally be broken down into two types: transfer learning for process of feature extraction and transfer learning with parameter fine-tuning. Both of these categories exist alongside one another.

If transfer learning is used for feature extraction, then a classifier that can detect fires will have to be trained from scratch on the top layer of the model that has already been pre-trained. The fire feature representation learned from the pre-trained phase is then utilized as a feature extractoion from the newly acquired fire image dataset. It is optional to retrain the entire model because the initial layers of a pre-trained model that detect fires are typically used to extract common fire features such as outlines. This eliminates the need. Transfer learning with fine-tuning involves adjusting various parameters in conjunction with the incorporation of newly discovered classifiers. The goal of the fine-tuning operation is to adjust certain features following the fire image data provided to make the learning process more efficient and accurate.

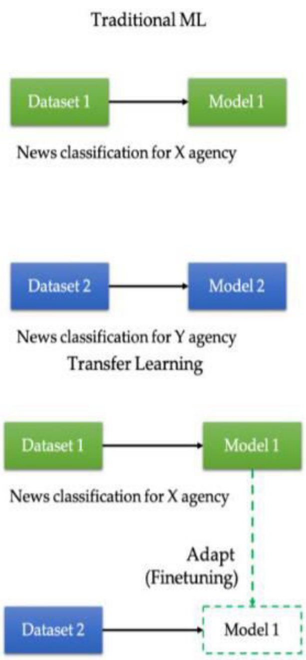

Figure 9. Comparison of Traditional with Transfer Learning [29]

MobileNet

In the second experiment, we used MobileNet. The MobileNet has a parameter set, including batch size with value of 32, input-shape with value of (224, 224, 3), epoch with value of 50, optimizer with value of Adam, and learning rate with value of 0.0001. To measure the Xception performance, we used accuracy, precision, recall, and F1-score. Based on the experiment, MobileNet obtained a better result than Xception. The result of the accuracy of MobileNet can be seen in **Figure 10**.

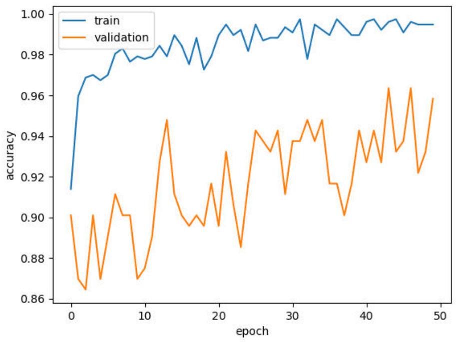

Figure 10. Accuracy of MobileNet

MobileNet with CLAHE

In the second experiment, we used the MobileNet with CLAHE. The contrast problem of of fire dataset is the main reason to optimize MobileNet with CLAHE. Method of CLAHE is a technique used for image quality improvement. CLAHE is effective in enhancing the contrast of images while avoiding over-amplification of noise. It has been shown to advance the quality of images in low-light conditions. The technique achieves this by performing histogram-equalization on the image, which improves the brightness and contrast of data. The pseudocode of the proposed model is presented in **Figure 11**.

Based on the experiment, MobileNet with CLAHE obtained 99,66% accuracy in the test phase. In the same phase, MobileNet with CLAHE obtained a value of F1-score of 1.00, the value of precision of 0.99, and a value of recall of 1.00. If compared to other model performances, MobileNet with CLAHE obtained the best result. The comparison of model performance for forest fire detection is presented in **Table 1**.

Pseudocode: MobileNet with CLAHE

```
input: image input x, classifier l, iterations t, clip limit cl, tileGridSize tg,
         midGamma mg
output: result R

def GCLAMNET(x):
     cl = 1.0, tg = (20,20)
     for i = 1 to t
     resize.xᵢ ← image.resize()
     grayscale.xᵢ ← image.convertColour(RGBtoGray)
     gclamnet.xᵢ ← image.convert(cl, tg, mg)
     model add ←  global average pooling
     model add ←  flatten
     model add ←  dense ReLU
     model add ←  dense ReLU
     model add ←  dense softmax
     R = processing data using classifier l on xᵢ
     end for
end
```

Figure 11. Pseudocode of MobileNet with CLAHE

Table 1. Comparison of model performance

Source	Model	Accuracy (%)	Improvement
[10]	Inception-v3	80,86	-
[10]	Inception-v4	83,25	↑ 2,39
[10]	ResNet-50	85,64	↑ 2,39
[10]	ResNet-26	86,66	↑ 1,02
This research	Xception	91,43	↑ 4,77
[11]	Faster RCNN	93,70	↑ 2,27
[12]	Densenet-201	98,46	↑ 4,76
This research	MobileNet with CLAHE	99,66	↑ 1,20

To explore the false or true positive error and the false or true negative error, the experiment is also analyzed using a confusion matrix. The confusion matrix of MobileNet with CLAHE is depicted in **Figure 12**.

	Fire	Non-Fire
Fire	224	1
Non-Fire	0	67

Figure 12. Confusion Matrix of MobileNet with CLAHE

In the prediction results from 224 images, only one image on wrongly predicted, namely the non-fire image, which was incorrectly expected to fire. Then, MobileNet with CLAHE can predict all the non-fire non-fire images in the testing phase. The example of the prediction of MobileNet with CLAHE is depicted in Figure 13.

**blue: correct; red: incorrect*

Figure 13. Prediction of MobileNet with CLAHE

Data that the model identifies as positive and positive are both referred to as true positive data (matches a fire or non-fire label and is a true match). The term "false negative data" refers to information that the model identifies as "negative data," but which is, in fact, "positive data" (detected does not match a fire or non-fire label but should match). Finally, the term "true negative data" refers to information that has been identified as "negative data" by the model, and it is accurate in describing the information as "negative data" (detected does not match a fire or non-fire label and indeed does not match).

CONCLUSION

Early warning of a fire disaster can be a solution for promptly providing information on the location and intensity of fires. This research sought to evaluate the implementation of Xception and MobileNet on a dataset of forest fire images and also examined the contrast enhancement and data augmentation method to solve the problem of forest fire images. Based on the experiment, MobileNet with CLAHE obtained 99,66% accuracy in the test phase. In the same phase, MobileNet with CLAHE obtained a value F1-score of 1.00, a value of precision of 0.99, and a value of recall of 1.00. If compared to other model performances, MobileNet with CLAHE obtained the best result. The future research of this research be implemented in real systems using private data. The model be modified to accelerate accuracy and reduce overfitting.

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