International Journal of Fire Science and Engineering, Vol. 36, No. 3, pp. 51-61, 2022 eISSN : 2950-8991
DOI: https://doi.org/10.7731/KIFSE.cb750817

Research Paper

Fire Image Classification Based on Convolutional Neural Network for Smart Fire Detection

Joohyung Roh, Yukyung Kim, Minsuk Kong†

Department of Equipment and Fire Protection Engineering, Gachon University, 1342 Seongnamdaero, Sujeong-gu, Seongnam-si, Gyeonggi-do 13120, Republic of Korea

(Received September 5, 2022; Revised September 16, 2022; Accepted September 16, 2022)

Abstract: This study investigated the effect of the class number on the prediction performance of the convolutional neural network (CNN) classification model that is applied in fire detectors to reduce nuisance fire alarms by appropriately recognizing fire images including those of flames and smoke. A CNN model trained by transfer learning using five image datasets of flame, smoke, normal, haze, and light was realized and trained by altering the class number to generate the classification model. A total of three classification models were generated as follows: classification model 1 was trained using normal and fire images including flames and smoke; classification model 2 was trained using flame, smoke, and normal images; and classification model 3 was trained using flames, smoke, normal, and haze, and light images. A test image dataset independent of training was used to assess the prediction performance of the three classification models. The results indicate that the prediction accuracy for classification models 1, 2, and 3 were approximately 93.0%, 94.2%, and 97.3%, respectively. The performance of the predicted classification improved as the class number increased, because the model could learn with greater precision the features of the normal images that are similar to those of the fire images.

Keywords: Fire image classification; Convolutional neural network; Fire detection; VGG 19; Accuracy

1. Introduction

Phenomena of Urbanization, densification, and skyscraperization led by rapid economic and industrial growth have been causing lots of human and property damage in fire safety accidents. The best way to prevent or reduce damage from complex and large-scale fire safety accidents is to detect and suppress them at the early stage of fire growth. Therefore, the fire detection technology in the automated fire alarm systems is promising and various researches are being conducted. In general, fire detectors detect fires using sensing heat, smoke, and flames generated by fires. Many studies on the demonstration of fire detector sensing a single object and the development of complex fire detectors by utilizing flame and gas detection or infrared and ultraviolet fire detection are also being actively conducted[1-4]. However, it is still required to solve the cost and technical problems including malfunction caused by contamination, limitation of detection range especially in open spaces.

Fire detection technology based on fire image features by applying advanced computer vision techniques has been proposed to overcome the limits of traditional fire detection methods. In computer vision, image color is a salient feature for detecting fires, and the detection of flames or smoke according to based on color features in space by using different color formats such as RGB, YCbCr etc. has been widely studied[5,6]. Owing to the fires occurred in various surroundings, the colors of flames and smoke images can vary depending on the surrounding environment. In addition, there was a limit to detect fire by using only color because of existence of objects or phenomena having similar color to flame and smoke. Thus, many fire detection researches with different ways such as characterizing smoke behavior characteristics by using optical flow, using wavelets making images blurred by smoke, and detecting region changes in flame or smoke have been conducted[7,8] but there is a limit to be widely used. Recently, the convolutional neural network (CNN) with great prediction performance that can extract the region features of the images was used to overcome the shortcoming of the machine learning model for image classification that cannot recognize the relationship between pixels in three-dimensional space[9]. Many studies has been conducted

Corresponding Author, TEL: +82-31-750-5715, FAX: +82-31-750-8749, E-Mail: mskong@gachon.ac.kr

to overcome the challenges such as requiring large amounts of high-quality image data and significant computational time to improve the fire prediction performance by using CNN models in various scenarios.

Lee et al.[10] evaluated the effect of applying the existing data preprocessing and feature extraction methods to CNN on the fire prediction performance. The model that was trained using the preprocessed image data showed improvements in the speed of calculation but decreased the fire prediction performance owing to information loss during preprocessing. Kim et al.[11] reported a decrease in detection performance due to discontinuous image frame collection derived from network problems or misrecognition of similar entities owing to user-defined algorithm development of existing video-based fire detection systems. In order to solve the above-mentioned problems, the authors proposed CNN model trained by using data representing the region of fire. The performance assessment of the proposed fire detection method showed an average detection rate of 99.05%, which was greater than that of previous research method. Kim and Kim et al.[12] proposed a fire detection system that simultaneously predicts flames and smoke using a CNN model to predict fires and visualize the location of flames or smoke using Grad-CAM. Based on the comparison analysis on the performance of CNN models such as Inception V3, Xception, Inception ResNet V2, it was confirmed that the Inception ResNet V2 model showed the best prediction accuracy, and the prediction accuracies for flame and smoke were 98.73% and 95.77%, respectivley. Majid et al.[13] used the algorithm of the CNN model to detect fire, proposed the visualization of the location of fire using the Grad-CAM algorithm, and comparatively analyzed the performance of the four models VGG16, GoogleNet V3, ResNet 50, and EfficientNet B0. The results showed that the prediction performance of EfficientNetB0 was superior, and the accuracy and recall were 95.4% and 97.61%, respectively. Lee and Shim[14] used the frame similarity before and after the use of deep learning to reduce the rate of false detection when the images having similar features with fire exists in the frame. Jo et al.[15] used the CNN algorithm trained by data including three representative causes of electric fire such as primary short-circuit traces, secondary short-circuit trances, and heat traces and verified its performance. Test results showed that the prediction accuracy of the cause of electric fires was approximately 86%, and this detection was more accurate and faster than existing visual classification method or material analysis methods. To overcome reduced prediction performance resulting from differences in the fire image dataset and actual fire images, Sharma et al.[16] (year) demonstrated improved prediction performance by increasing the depth of the CNN layer through fine-tuning and proposing training with a dataset that includes a relatively large number of non-fire images. Huang et al.[17] proposed a new wavelet-CNN technique that applied a two-dimensional (2D) Haar transformation to extract the spectral features of an image in order to improve the prediction accuracy of the previous CNN model. They comparatively analyzed the two existing models, ResNet50 and MobileNet v2. They confirmed that the new wavelet technique was practical because the calculation was fast and fire detection accuracy was high. Ryu et al. (year) proposed a fire detection method using a CNN model by extracting the moving object as the area of interest[18]. Compared with the method of extracting the location of the object from the entire area, the calculation time was reduced. In addition, using flame, smoke, and haze image datasets, fire detection was observed with high prediction performances at an average accuracy of 92.3% and an average precision of 93.5%. With a YOLO network, Huang et al.[19] quantified aspects such as the location of flame spread, speed of flame spread, and flame thickness, which represent the features of fire development. In addition, they proposed a new method for predicting fire development using the ResNET model, and assessed the performance based on electric wire fire experiments. Li et al.[20] proposed a method of using object detection CNN models to improve the prediction accuracy and calculation time of the existing fire detection algorithm. Based on the evaluation of the performances of Faster-RCNN, R-FCN, SSD, and YOLO v3, it was determined that YOLO v3 was most appropriate for actual fire detection owing to its superior fire detection performance, great robustness, and fast detection speed.

Overall, most existing studies have involved classification through flame and smoke visualization after the CNN algorithm-based detection of fire location, derivation of an optimal model via the application and comparison of various CNN models, and improvement of performance through image processing. Most assess the prediction performance of the fire image classification models trained by using flames and smoke images. Therefore, to improve the performance of the fire classification model, this study entailed an analysis of the effect of the change in the class number of the classification model on the prediction performance of the fire classification by training not only with flame and smoke images that represent fire but also with the addition of images similar to fire as a class. Then, the prediction performance and characteristics of the three classification models were comparatively analyzed. The classification models include one that was trained with fire images containing both flame and smoke and normal images, another that was distinctly trained with flame, smoke, and normal images, and the las that was trained with flame, smoke, normal images as well as light, and haze images that are similar to flame and smoke images respectively.

2. Methodology

This study analyzed the effect of the class number of the classification model on the prediction performance to reduce nuisance alarms by the appropriate recognition of flame and smoke images that represent fire. As shown in Figure 1, the image classifiers were classified into three types for ease of comparison of prediction performance. The fire image classifier designated as classifier 1 utilized a dataset with fire images, which include flame and smoke, and normal images, fire image classifier 2 utilized a dataset including flame, smoke, and normal images, and fire image classifier 3 utilized a dataset including flame, smoke, normal, haze, and light images. For each of the five classes of flame, smoke, normal, haze, and light, a dataset of 1,000 original images was used, and a total of 5,000 images were used. Therefore, depending on the number of classification classes that were used, 3,000, 3,000, and 5,000 original images were used for classifiers 1, 2, and 3, respectively. To accurately examine the performance of each classifier, the ratio of the training dataset (Train), validation dataset (Valid) that assesses the prediction performance of the model during training, and test dataset (Test) for evaluating the final model was set to 7:1.5:1.5. The pretrained CNN model was re-trained with the fire-related images and the best performing model was selected. The prediction performance of the fire image classifier with the selected model was assessed using the test dataset images. The overall fire image classification process is presented in Figure 2.

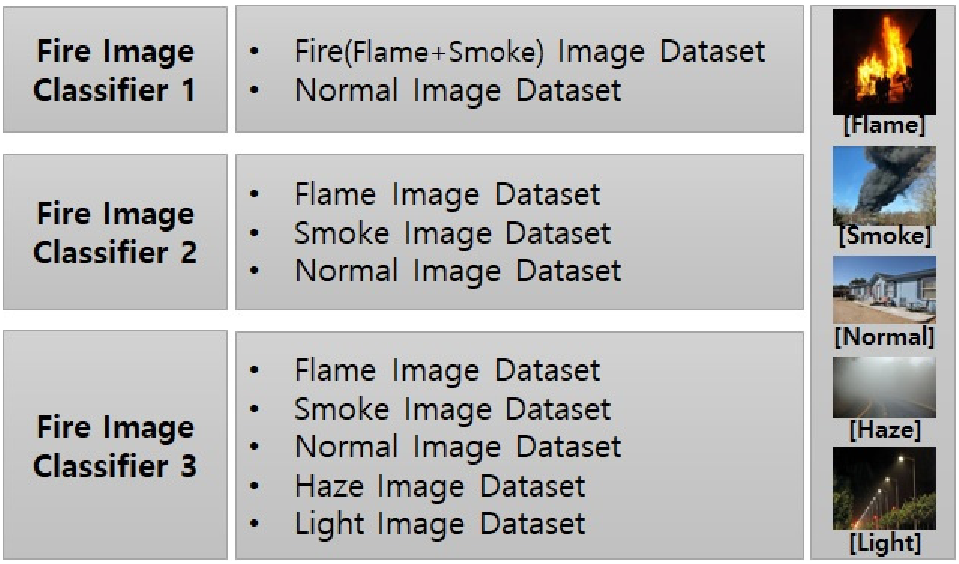

Figure 1. Datasets used for fire image classifiers.

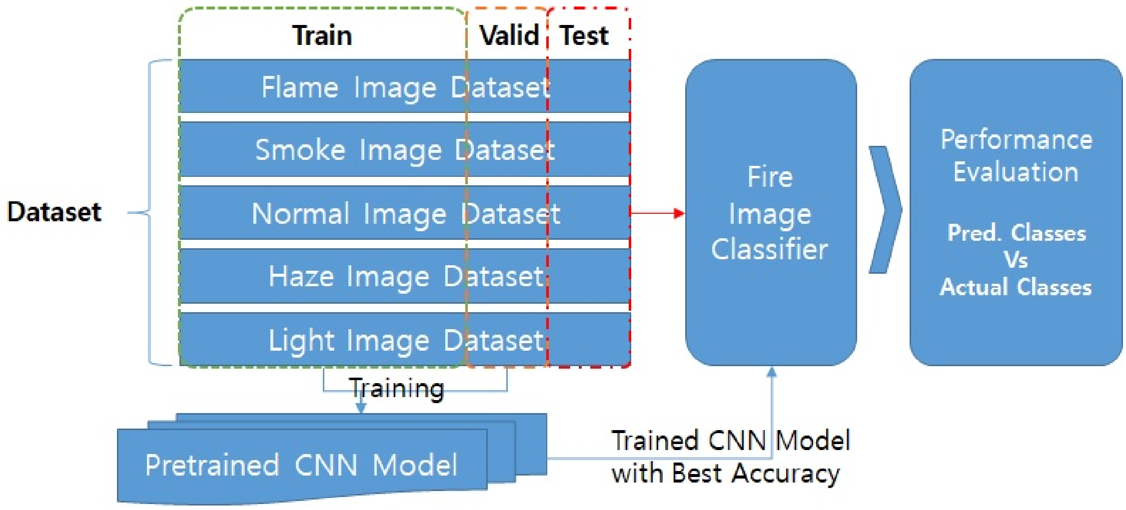

Figure 2. Flow chart of fire image classification.

In image classification, machine-learning models have set the input variable as an independent variable and flatten the image pixel value into a vector for use. In this case, the relationship between pixels according to the space could not be considered, for which a CNN model that reflects region feature was proposed. Owing to continuous development in algorithms and hardware, in the field of computer vision, this algorithm is one of the most commonly used among deep learning models that uses images and videos. The CNN is composed of an input and output layer and several hidden layers in between, as shown in Figure 3. CNNs train in a manner in which the major features of an image could be detected through the convolution layer, which activates the region feature of an image, and the pooling layer, which improves the speed of learning by reducing the feature map dimension and ultimately the number of learning parameters. In addition, a fully connected layer in the classification layer probabilistically classifies the class according to each image for the final classification output. Substantial amounts of image data are required to create a well-trained CNN model for the classification of images in a certain field, and data organization and training are time-consuming. To address such drawbacks, a classification model that was well-trained using large amounts of image data was obtained for use of transfer learning that proceeds with training for a new classification. Transfer learning is widely adopted as a useful method as it is considered advantageous owing to its effective training capability and achievement of high accuracy with little training data.

In this study, the Visual Geometry Group (VGG) model, which has a relatively simple structure using deep layers, and which is known for its outstanding cross-sectoral applicability and prediction performance, was used to perform transfer learning. The structure of the VGG 19 model used in this study is depicted in Figure 4. A 244 × 244 and RGB input image dataset was constructed through preprocessing as the class training dataset, and the "Train" and "Valid" image data of Figure 1 were used for training. For transfer learning, a well-trained VGG 19 model was obtained for its image feature extraction capability. The model was re-trained with a dataset that was prepared for fire image classification by altering the last output layer. For multiclass classification, the cross-entropy loss function was utilized, and the stochastic gradient descent was applied for optimization. The Python programming language was used for implementing the classification model, with the open-source machine-learning library PyTorch, and a computer equipped with an Intel® Core™ i9-10980XE processor and GeForce RTX 3080 was used for training and performance assessment.

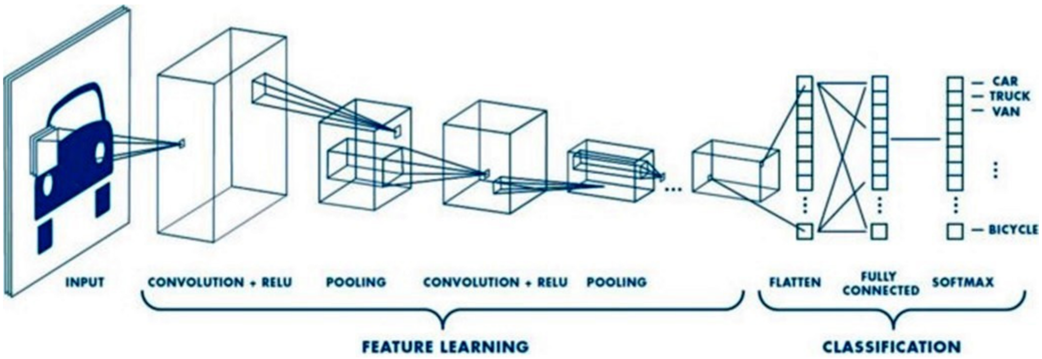

Figure 3. Convolutional neural network architecture[21].

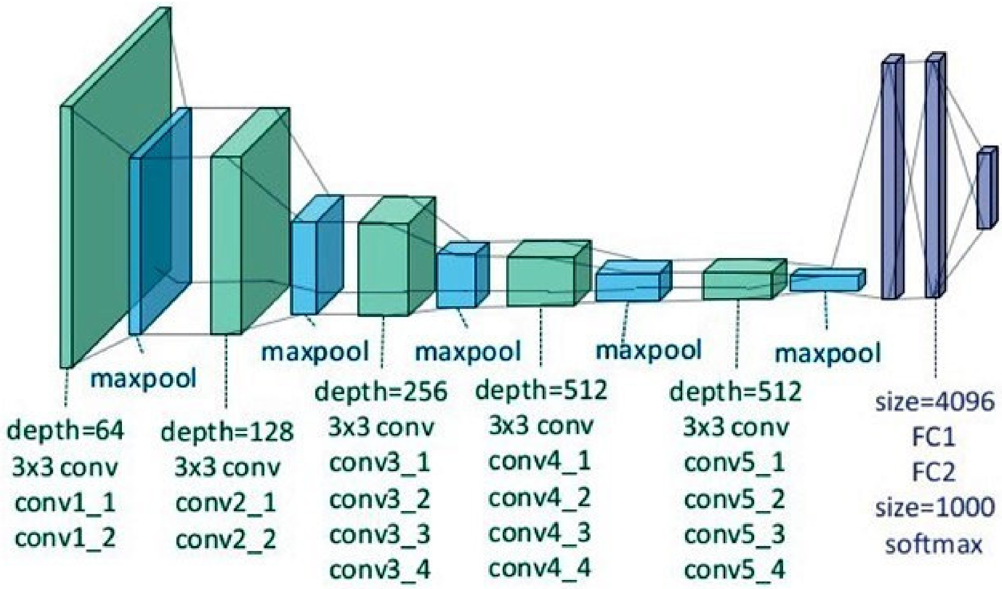

Figure 4. VGG 19 architecture[22].

3. Results and Discussion

In this study, three fire image classifiers with maximum prediction performances were derived by training with distinct class numbers. A total of 150 images were used for each class to assess the prediction performance. A confusion matrix was used to assess the performance of the image classification models and to determine the prediction tendency. The precision, recall, and accuracy were used for the quantitative performance analyses. The four types of probable predictions from two classes are summarized in Table 1. Based on fire detection and the assumption of a classification model that classifies fire (positive) and non-fire (negative), true negative (TN) was shown in the case of a true prediction of an actual non-fire, and true positive (TP) was shown in the case of a true prediction of an actual fire. False negative (FN) was shown to indicate the false prediction of an actual fire to non-fire, and false positive (FP) was shown to indicate a false prediction of an actual non-fire to fire.

Table 1. Possible Image Classification Outputs

		Predicted	
		Negative	Positive
Actual	Negative	True negative (TN)	False positive (FP)
	Positive	False negative (FN)	True positive (TP)

Based on the results of Table 1, *Precision, Recall, and Accuracy* were determined using the following equations:

$$\mathrm{Precision} = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

A fire image classifier that was trained with a dataset consisting of fire images that include flame and smoke and normal images (non-fire) was used to assess the prediction performance for the test images. The results are presented as a confusion matrix in Table 2. The precision which represents the rate of an actual fire among test images predicted as a fire, was approximately 90.0%. The recall, which is the rate of an actual fire predicted as a fire, was approximately 96.7%. The accuracy, which represents the rate of correct prediction by the classifier for all test images, was approximately 93.0%. To ascertain the prediction characteristics of classifier 1, cases where the classifier incorrectly predicted were analyzed based on the confusion matrix. The representative images incorrectly predicted are shown in Figure 5. First, the case of predicting fire as a normal (non-fire) state was either a misdiagnosis of haze, which is similar to smoke, or a blurry smoke image. Such a result was attributed to the absence of a clear recognition of the smoke image features because the classification model was trained with a dataset containing mixed flame and smoke images. This is also because the haze images similar to the smoke images have caused the misdiagnosis. Among the erroneous predictions, cases where normal images were predicted as fires were relatively abundant. Data showed that most of these images were light images including streetlights, road signs, and sunlight, clouds images and haze images. This is attributed to the lack of precise information on the characteristics of the objects or phenomena having similar features with the fire images. Therefore, training with images similar to fires, such as light, haze, and cloud, was considered necessary to improve the prediction performance of fire image classification.

Table 2. Confusion Matrix for Classifier 1

		Predicted (P)	
		Fire (F)	Normal (N)
Actual (A)	Fire (F)	145	5
	Normal (N)	16	134

Figure 5. Prediction results of classifier 1.

The second classifier was trained for three class types, consisting of flame images, smoke images and normal images, for the use of a model with the optimum prediction performance. The results of the predicted performance for the test images are shown in the confusion matrix in Table 3. The erroneously predicted images were analyzed to determine the specific features of the classification model's prediction, and the representative images are shown in Figure 6. In the case of flame image prediction, the precision and recall were good at approximately 94.0% and 94.7%, respectively. In the case of flame images, most were erroneously predicted as smoke because of the flame and smoke presented in one image. Moreover, blurry images due to color changes tended to be predicted as smoke. Therefore, to enhance the prediction performance, a consideration of this tendency is required for future model training. The precision and recall for normal image prediction were 98.5% and 88.7%, respectively, and the recall was relatively low. Among those predicted as a normal image, the probability of true prediction was high, but the prediction performance for a normal image was found to be low. The incorrect predictions for the normal images were cases where streetlights, light on road signs, and sunlight were recognized as a flame, while haze or clouds caused by climate conditions were mistakenly predicted as smoke images. Therefore, it is necessary to perform training for object images having similar colors to flame and smoke. In the case of smoke, the precision and recall were approximately 90.9% and 99.3%, respectively. The classifier used in this study accurately predicted actual smoke images. However, the precision was relatively low because of incorrectly recognizing images with the presence of both flame and smoke in one image or haze and cloud having similar features to smoke. In conclusion, classifier 2 had a prediction accuracy of approximately 94.2%, which was a slight increase in prediction performance compared with classifier 1 owing to the increase in the training class. Nonetheless, there was a low prediction performance for image shade, changes in color, and blurred images, lightened images, and images having similar features to fire images.

Table 3. Confusion Matrix for Classifier 2

		Predicted (P)		
		Flame (F)	Normal (N)	Smoke (S)
Actual (A)	Flame (F)	142	1	7
	Normal (N)	9	133	8
	Smoke (S)	0	1	149

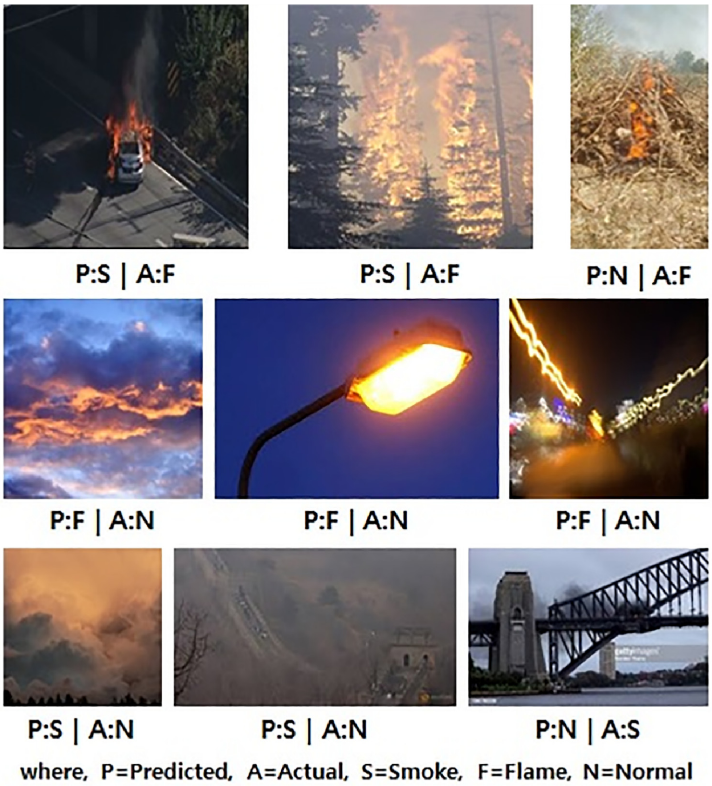

Figure 6. Prediction results of classifier 2.

The analysis of the prediction performance was conducted with classifier 3 trained with images of five classes including flame, smoke, normal, haze, and light images. The results of the classifiers' prediction are presented in a confusion matrix in Table 4. The images incorrectly predicted were analyzed to ascertain specific characteristics of prediction of the classification model, and the representative images incorrectly predicted are shown in Figure 7. The precision and recall for fire image prediction were high at approximately 98.6% and 96.0%, respectively. Overall the number of predicting the flame as the smoke was reduced but there was a low prediction performance in the cases including the image containing both the flame and smoke and the shaded or lightened image. In the case of normal image prediction, the precision and recall were high at approximately 97.4% and 99.3%, respectively. In particular, the recall was improved as compared with classifier 2. Such results were considered to have been achieved by additional training with haze and light, which are similar to fire. In the case of smoke image prediction, the precision and recall were approximaltely 94.2% and 97.3%, respectively. The precision was improved compared with classifier 2. However, the recall was determined to have relatively deteriorated as featuring haze, which has similar characteristics to smoke, into a single class resulted in a greater confusion in image classification. The haze image prediction performance was high, with the precision and recall at approximately 96.8% and 99.3%, respectively. The precision was improved compared with classifier 2 but the recall was lower because featuring the haze having similar characteristics of smoke resulted in a confusion of image classification. The haze images were well predicted, and the precision and recall were approximately 96.8% and 99.3%, respectively. There was a great performance in predicting the light images and the precision and recall were about 100% and 94.7%, respectively. The number of erroneous predictions was low, but erroneous predictions were evenly distributed throughout the remaining four classes. Images containing strong red light similar to flames were recognized as flame, and blurry light images were recognized as haze or smoke. Overall, classifier 3 showed a prediction accuracy of approximately 97.3%, which was the highest performance among the classifiers. The training of images that have similar features to flame and smoke, representing fire was considered to have improved the prediction performance. However, the prediction performance remained low in the prediction cases of blurred or lightened images and images having strongly similar features to fire images. Therefore, future studies will be conducted to enhance the prediction performance by using data augmentation, preprocessing images, etc. and to verify the prediction models by using images from various fire scenarios.

Table 4. Confusion Matrix for Classifier 3

		Predicted (P)				
		Flame (F)	Normal (N)	Smoke (S)	Haze (H)	Light (L)
Actual (A)	Flame (F)	144	1	5	0	0
	Normal (N)	1	149	0	0	0
	Smoke (S)	0	1	146	3	0
	Haze (H)	0	0	1	149	0
	Light (L)	1	2	3	2	142

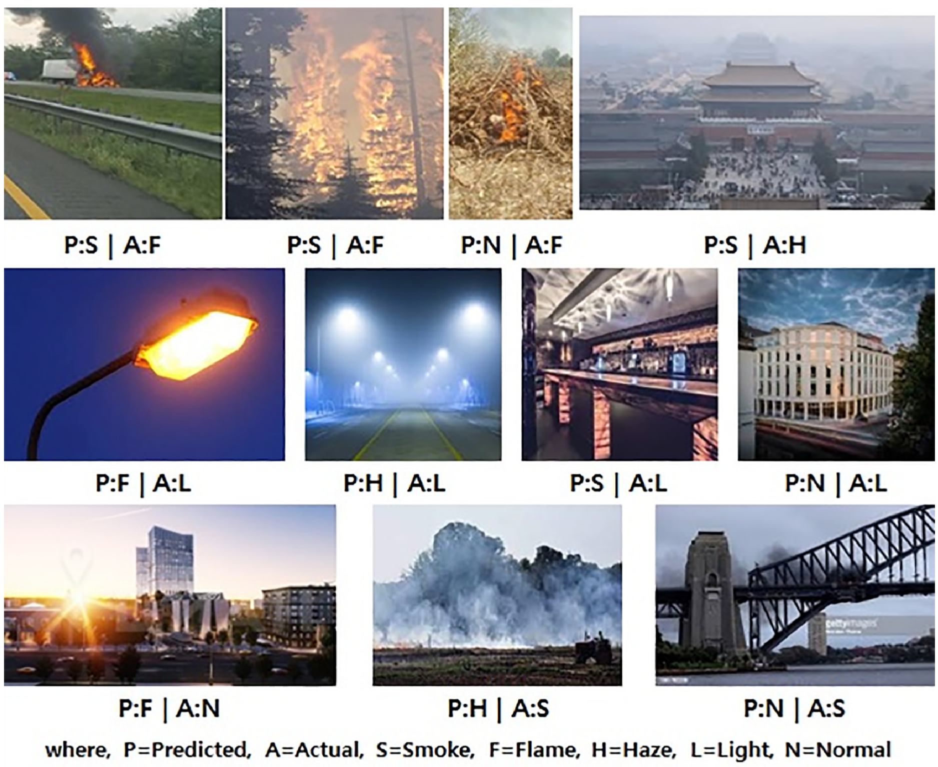

Figure 7. Prediction results of classifier 3.

4. Conclusions

This study examined the effect of the class number on the prediction performance of a CNN classification model for the fire detection systems. The fire image prediction classifier was classified as classifier 1, which was trained using a dataset consisting of fire (flame and smoke) and normal images, classifier 2, which was trained using a dataset consisting of flame, smoke, and normal images, and classifier 3, which was trained using a dataset consisting of flame, smoke, normal, haze, and light images. The results of the prediction performances of the three classifiers were comparatively analyzed. The prediction accuracy of classifier 1 was approximately 93.0%, and images containing features similar to fire, such as light and haze, were erroneously predicted as flame and smoke, respectively. The prediction accuracy of classifier 2 was approximately 94.2%, which was slightly greater than that of classifier 1 because of the effect of training with fire classified into flame and smoke. However, the classification performance remained low for light and smoke images, as well as blurred and lightened images. The highest prediction accuracy was achieved by classifier 3 at 97.3% indicating that training with light and haze images having features similar to flame and smoke improved the prediction accuracy. Nonetheless, there were incorrect predictions in the cases including images having high similarity to fire and lightened and blurred images. Future studies will be performed to verify the performance of the classification model and to improve the prediction performance by using using images related to various fire scenarios.

Author Contributions

Conceptualization and methodology, J.R., Y.K., and M.K.; formal analysis and investigation, J.R. and Y.K.; writing—original draft preparation, J.R.; writing—review and editing, Y.K. and M.K.; supervision, M.K. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. S. H. Park and J. C. Cho, "A Study on the Development of the Single Station Fixed Temperature Detector of Low Power Consumption for Residential Fire Prevention", Fire Science and Engineering, Vol. 24, No. 6, pp. 61-68 (2010).
2. B. K. Seo and S. G. Nam, "Study of the Improvement of False Fire Alarms in Analog Photoelectric Type Smoke Detectors", Fire Science and Engineering, Vol. 30, No. 5, pp. 108-115 (2016). https://doi.org/10.7731/KIFSE.2016.30.5.108
3. C. H. Park, Y. H. Kang, M. S. Jang, H. J. Seo, and Y. M. Kim, "A Smart Fire Detector System for Fire Prevention", Proceedings of the Korean Society of Computer Information Conference, Vol. 30, No. 1, pp. 293-294 (2022).
4. N. Y. Ko, B. H. Lim and D. J. Seo, "Development of Ultraviolet Infrared Flame Detector for Fire Detection", Proceedings of the Korean Society of Mechanical Engineers Fall Conference, pp. 68-73 (2006).
5. Y. H. Kim, A. Kim and H. Y. Jeong, "RGB Color Model Based the Fire Detection Algorithm in Video Sequences on Wireless Sensor Network", International Journal of Distributed Sensor Networks, Vol. 10, No. 4, p. 923609 (2014). https://doi.org/10.1155/2014/923609
6. C. E. Premal and S. S. Vinsley, "Image Processing Based Forest Fire Detection using YCbCr Colour Model", 2014 International Conference on Circuits, Power and Computing Technologies, pp. 1229-1237 (2014). https://doi.org/10.1109/iccpct.2014.7054883
7. S. Rinsurongkawong, M. Ekpanyapong, and M. N. Dailey, "Fire Detection for Early Fire Alarm Based on Optical Flow Video Processing", 2012 9th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, pp. 1-4 (2012). https://doi.org/10.1109/ecticon.2012.6254144
8. S. Verstockt, I. Kypraios, P. De Potter, C. Poppe and R. Van de Walle, "WaveletBbased Multi-Modal Fire Detection", 2011 19th

European Signal Processing Conference, pp. 903-907 (2011).
9. S. Sharma and K. Guleria, "Deep Learning Models for Image Classification: Comparison and Applications", 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering, pp. 1733-1738 (2022).
10. J. H. Lee, B. M. Kim and Y. S. Shin, "Effects of Preprocessing and Feature Extraction on CNN-based Fire Detection Performance", Journal of the Korea Industrial Information Systems Research, Vol. 23, No. 4, pp. 41-53 (2018). https://doi.org/10.9723/jksiis.2018.23.4.041
11. Y. J. Kim and E. G. Kim, " Image based Fire Detection using Convolutional Neural Network", Journal of the Korea Institute of Information and Communication Engineering, Vol. 20, No. 9, pp. 1649-1656 (2016). https://doi.org/10.6109/jkiice.2016.20.9.1649
12. Y. J. Kim and E. G. Kim, "Real-Time Fire Detection based on CNN and Grad-CAM", Journal of the Korea Institute of Information and Communication Engineering, Vol. 22, No. 12, pp. 1596-1603 (2018). https://doi.org/10.6109/jkiice.2018.22.12.1596
13. S. Majid, F. Alenezi, S. Masood, M. Ahmad, E. S. Gunduz and K. Polat, "Attention based CNN Model for Fire Detection and Localization in Real-World Images", Expert Systems With Applications, Vol. 189, p. 116114 (2022).
14. Y. H. Lee and J. C. Shim, "False Positive Fire Detection Improvement Research using the Frame Similarity Principal based on Deep Learning", Journal of Institute of Korean Electrical and Electronics Engineers, Vol. 23, No. 1, pp. 242-248 (2019). https://doi.org/10.7471/ikeee.2019.23.1.242
15. J. H. Jo, J. H. Bang, J. H. Yoo, R. B. Sun, S. J. Hong and S. B. Bang, "A CNN Algorithm Suitable for the Classification of Primary and Secondary Arc-Bead and Molten Mark using Laboratory Data for Cause Analysis of Electric Fires", The Transactions of the Korean Institute of Electrical Engineers, Vol. 70, No. 11, pp. 1750-1758 (2021). http://doi.org/10.5370/KIEE.2021.70.11.1750
16. J. Sharma, O. Granmo, M. Goodwin and J. T. Fidje, "Deep Convolutional Neural Networks for Fire Detection in Images", Engineering Applications of Neural Networks, Vol. 744, pp. 183-193 (2017). https://doi.org/10.1007/978-3-319-65172-9_16
17. L. Huang, G. Liu, Y. Wang, H. Yuan and T. Chen, "Fire Detection in Video Surveillances using Convolutional Neural Networks and Wavelet Transform", Engineering Applications of Artificial Intelligence, Vol. 110, p. 104737 (2022). https://doi.org/10.1016/j.engappai.2022.104737
18. J. K. Ryu and D. K. Kwak, "A Study on Flame and Smoke Detection Algorithm Using Convolutional Neural Network Based on Deep Learning", Journal of The Korean Society of Hazard Mitigation, Vol. 20, No. 1, pp. 223-232 (2020). https://doi.org/10.9798/KOSHAM.2020.20.1.223
19. P. Huang, M. Chen, K. Chen, H. Zhang, L. Yu and C. Liu, "A Combined Real-Time Intelligent Fire Detection and Forecasting Approach Through Cameras Based on Computer Vision Method", Process Safety and Environmental Protection, Vol. 164, pp. 629-638 (2022). https://doi.org/10.1016/j.psep.2022.06.037
20. P. Li and W. Zhao, "Image Fire Detection Algorithms Based on Convolutional Neural Networks", Case Studies in Thermal Engineering, Vol. 19, pp. 100625 (2020). https://doi.org/10.1016/j.csite.2020.100625
21. S. Saha, "A Comprehensive Guide to Convolutional Neural Networks — the ELI5 Way", Towards Data Science, (December 16, 2018). https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53.
22. Y. Zheng, C. Yang and A. Merkulov, "Breast Cancer Screening using Convolutional Neural Network and Follow-Up Digital Mammography", Proceedings of SPIE 10669, Computational Imaging III, pp. 1066905 (2018). https://doi.org/10.1117/12.2304564