2019 6th IEEE International Conference on Engineering Technologies and Applied Sciences (ICETAS)

Machine Learning Applications for Fire Detection in a Residential Building

Ngonidzashe A Mwedzi; Nnamdi I. Nwulu and Saheed Lekan Gbadamosi
Department of Electrical and Electronic Engineering Science,
University of Johannesburg
South Africa
218099241@student.uj.ac.za; nnwulu@uj.ac.za; sgbadamosi@uj.ac.za

***Abstract*— Fire is one of the most serious accidents that can occur in houses, schools, offices and companies. This can lead to several losses, causalities and serious equipment damages. It is highly essential to put in place advanced disaster response mechanisms in order to safeguard against fire disaster in our environment. Recently, modern buildings possess surveillance cameras for security purpose, such cameras can be utilized for fire detection in buildings. In this paper, deep learning and computer vision are applied for detecting fire incident in different systems. The proposed model utilizes an advanced image processing and classification algorithms via deep learning and convolutional neural networks (CNN) to improve the performance of residential fire alarms and eradicate nuisance alarm scenarios.**

Keywords*— *fire detection, Deep Learning, false alarm

I. Introduction

Fire is one of the major causes of financial losses and humanistic disaster in the world, which can occur in various environments such as schools, offices, companies, residential buildings, mines and forests. In order to minimize the harm caused by fire and reduces the financial losses attached, it is essential to prevent the spread of fire at the early stage. Fire detection is a vital key in surveillance system for monitoring environments as a means of timely warning to report the start of fire [1]. Most of the fire detectors make use of point sensors for measuring fire probabilities in a close range. In order to mitigate the triggering of false alarm of the fire detection system, the detector needs to differentiate the fire smoke from non-fire incident because triggering of false fire alarm can be very costly and also cause disruptions to production and services. Therefore, in order to overcome the inconveniences that is attached to false alarm from fire detection system, it is highly essential to examine the current available technology in fire detection, so as to provide reliable and effective system.

The development of deep learning, computer vision and digital camera technology has aided the use of intelligent video fire detection approach [2], thereby upgrading the fire detection systems to an intelligent and vision-based system. Reference [3 Brian] presents an experimental analysis using neural network approach for detecting and analyzing the fire and false alarm conditions. In the recent time, some researchers have worked on fire and smoke detection with computer vision [4] [5] [6] [7]. They focused on flame shape characteristics and color models; this approach uses cameras, intelligent techniques, wireless networks and image processing techniques. These are modeled and implemented for detecting fire incidences in the environment. Similarly, classification approach based on machine learning have been employed for fire detection problems in [8] [9]. In [10], contours and bounding boxes are used to indicate the fire pixels detection on an image. This mechanism distinguished if there exist more than a single fire in the image. Reference [11] develops an algorithm for extracting the data characteristics of fire such as smoke density, temperature and carbon monoxide density using a fuzzy system. Reference [12] proposes an artificial intelligence algorithm for fire detection using shape characteristics of fire from video footages. This paper presents a novel intelligent fire detection system method. A VGGNet architecture was derived from CNN network with the aim of achieving a good image classification performance, minimal false alarm and high fire detection rate.

II. IMAGE DATABASE

In this section, the structure of the proposed fire detection system approach is presented in Figure 1. The proposed structure has two approaches namely: fire detection based on object recognition approach and region classification based on image recognition approach. The image dataset is structured into three sets category [13][14]:

- Training image set: The set in this category contains 800 images, in which 200 images from each fire scenario as shown in Figure 1. These images are used in training the Neural Network for proper classification of each fire as shown in the scenarios.
- Testing image set: the set in this category contains 200 images and they are used for evaluating and assessing the efficiency and effectiveness of the trained Neural Network set of images as well as classifying the precise image at all time.

This dataset was built by downloading google images using the Google Custom Search Engine (CSE) API [15].

III. NEURAL NETWORK IMPLEMENTATION

The fire scenarios mentioned earlier were set as class labels of the data using a Label Binarizer. The images were randomly transformed by shearing and various rotations to generate more training data. This was done to add more data to learn from and prevent over fitting. The Neural Network was trained using 800 color images which were 96x96 pixels

978-1-7281-4082-7 /19/$31.00 ©2019 IEEE

a) Fire place fires

b) Kitchen fires

c) Candle lighting

d) Image with no fire

Fig 1: Example Images in the dataset

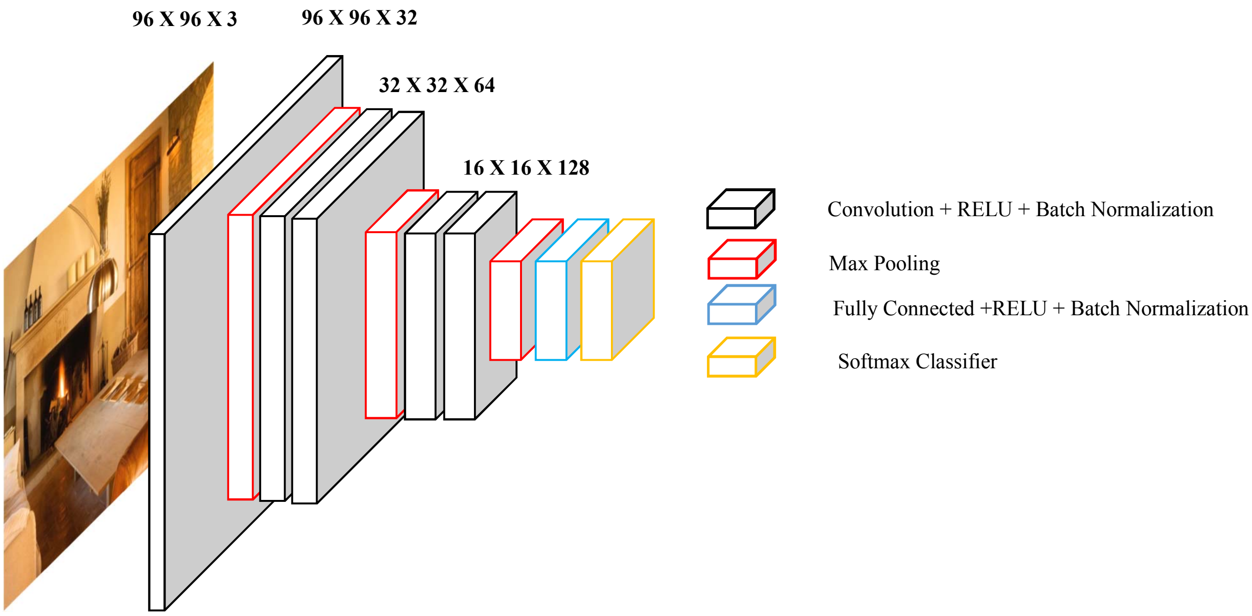

Fig 2. Illustration of a variant of the VGGNet

with a depth of 3 (RBG). All the images were resized to 96x96 pixels before being loaded to the neural network. The network's convolution layer consists of 32 filters and it utilizes a Rectified Linear Unit (RELU) as its activation function. This activation was normalized to increase the learning rate. As the Batches were trained, connections of nodes between layers were randomly disconnected. This is required in order to ensure that predictions are not influenced by individual nodes in the layers and the procedure is referred to as dropout. Filter size was changed from 32 to 64 to create more filters which can learn from smaller spatial dimensions when it gets more deeper in the network. The max pooling size was reduced from 3 x 3 to 2 x 2 to prevent rapid reduction in the spatial dimensions of the input volume. In order to prevent overfitting, 2 more layers of cconvolution and activation were added with a filter size of 128 before another pooling layer followed by more dropout. A set of fully connected layers with RELU activation is added, then Batch Normalization is performed again. Dropout was performed for the final time and the model was wrapped up with a Softmax classifier which returns each class label's probabilities.

The softmax function was used to find vector of scores and scaled it to a vector of values which are between 0 and 1. The probability distribution produced is given as:

$$e^{s_{y_i}} / \sum_j e^{s_j} \qquad (1)$$

The model was compiled using the Stochastic Gradient Descent (SGD) optimizer with categorical cross-entropy as the loss function.

Cross-entropy Loss

This loss shows the distance between the original distribution and the output distribution. The loss for each data point was calculated using the equation below.

$$L_i = -\log(e^{s_{y_i}}/\sum_j e^{s_j}) \quad (2)$$

The loss for all images in the training and validation set was calculated using equation 3

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i \quad (3)$$

Loss function

This defines how well class labels are predicted with labels reality. The small loss from the graph in Fig 3 signifies good agreement.

Scoring function $f(x_i)$ was used to map the images to class labels

$$f(x_i, W, b) = Wx_i + b \quad (4)$$

where W is the weight matrix and b is Bias vector. For simplicity, b is omitted and the equation in written as follows:

$$S_j = f(x_i, W) \quad (5)$$

The predicted score of the *j-th* class using the *i-th* data point leading to a similar predicted score of the y_i-th class (the correct class) written as S_{y_i}.

IV. RESULTS AND DISCUSSION

The model was trained for 73 iterations in 83 minutes and achieved a high accuracy of 85% with limited overfitting. These results were obtained using a core i7 Computer with 8 GB of RAM. The training loss and accuracy graph is shown Fig. 3. The small loss from the graph signifies good agreement.

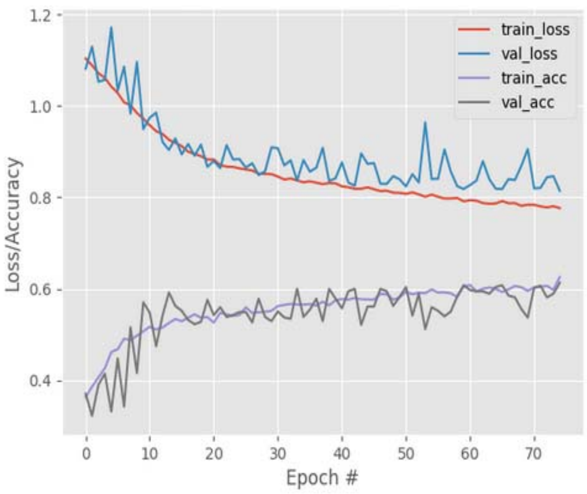

Fig. 3: Loss and Accuracy plot against the number of iterations

Classifier Performance Metrics

Precision This is the ratio of correct positive results to the number of all positive results which are returned by a classifier.

Recall this is the ratio of correct positive results to the number of all relevant samples.

F1 Score This is average of precision and recall. It must has a best value of 1 and worst of 0.

Table 1. Classifier Performance Metrics of the fire detector model

	Precision	Recall	F1-score
Kitchen Fire	0.81	0.80	0.84
Candle Fire	0.86	0.87	0.86
Kitchen Fire	0.83	0.81	0.83
No Fire	0.88	0.90	0.86
Average / Total	0.85	0.85	0.85

Table 1 gives the performance metrics for fire detection system and it can be seen that the network accuracy is 85%, showing that the network has been able to distinguished between the four classes of fires. These results obtained has the ability of minimizing the false fire alarms because of the high probability of randomly choosing the correct label for any specified picture.

V. CONCLUSION

This paper presents an intelligent fire detection system method via the use of computer vision and convolutional neural network to analyze the performance of the fire detection system under various setup scenarios. The dataset obtained from google image search were analyzed and trained. The efficiency and effectiveness of the trained neural network set of images are classified based on the precise images at the test stage. The simulation results demonstrate that the propose intelligent fire detection system has significant improvement as compared to non-intelligent mechanisms. Through the application of CNN and VGGNet techniques, the system obtained a better result with 85% system accuracy and minimizing false alarm.

REFERENCES

[1] F. Bu and M. S. Gharajeh, “Intelligent and vision-based fire detection systems: A survey,” Image Vis. Comput., 2019.

[2] H. Wu, D. Wu, and J. Zhao, “An intelligent fire detection approach through cameras based on computer vision methods,” Process Saf. Environ. Prot., vol. 127, pp. 245–256, 2019.

[3] B. J. Meacham, " The Use of Artificial Intelligence Techniques for Signal Discrimination in Fire Detection Systems.," Journal of Fire Protection Engineering, , p. 125–136, 1994.

[4] G. Healey, D. Slater, T. Lin and B. D. a. A. Goedeke, "A system for real-time fire detection," in Proc. Int. Conf. Comp. Vis. and Pat. Rec, pp. 605-606., 1993.

[5] J. R. Martinez-de Dios, B. C. Arrue, A. Ollero, L. Merino and F. Gómez-Rodríguez, "Computer vision techniques for forest fire perception," in Image Vision Comput vol. 26, pp. 550-562, 2008.

[6] T Celik and H Demirel, "Fire detection in video sequences using a generic color model," in Fire Safety J., vol. 44, no. 2, pp. 147-152, 2009.

[7] T. Chen, P. Wu and Y. Chiou, "An early fire-detection method based," in Proc. Int. Conf. on Image Proc, pp. 1707 -1710, 2004.

[8] B. Ko, K. Cheong and J. Nam, "Fire detection based on vision sensor and support vector machines," in Fire Safety J vol. 44, no. 3, p. 322–329. 2009.

[9] Ahmed, S. Faiz, et al. "Energy conservation and management system using efficient building automation." AIP Conference Proceedings. Vol. 1660. No. 1. AIP Publishing, 2015.

[10] Aditya Kakde, Nitin Arora, and Durgansh Sharma "Fire Detection System Using Artificial Intelligence Techniques", International Journal of Research in Engineering, IT and Social Sciences,Volume 08 Issue 11, pp 1-5,, 2018.

[11] S. Chen, H. Bao, X. Zeng, and Y. Yang, “A Fire Detecting Method Based on Multi-sensor Data Fusion,” in SMC’03 Conference Proceedings. 2003 IEEE International Conference on Systems, Man and Cybernetics. Conference Theme - System Security and Assurance, 2003, pp. 3775–3780.

[12] D. Zhang et al., “Image Based Forest Fire Detection Using Dynamic Characteristics With Artificial Neural Networks,” in 2009 International Joint Conference on Artificial Intelligence, 2009, no. 2, pp. 290–293.

[13] Nwulu N.I. and Fahrioglu. M., “A Neural Network Model for Optimal Demand Management Contract Design”, Proceedings of the 10th International Conference on Environmental & Electrical Engineering (EEEIC2011), Rome, Italy, 8-11 May 2011.

[14] Nwulu N.I. and Agboola P.O., “Modelling & Predicting Electricity Consumption Using Artificial Neural Networks”, Proceedings of the 11th International Conference on Environmental & Electrical Engineering (EEEIC2012), Venice, Italy, 18-25 May 2012.

[15] "GOOGLE CUSTOM SEARCH ENGINE," GOOGLE, [Online]. Available: https://cse.google. [Accessed 5 May 2019].