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A Lightweight CNN Model for Vision Based Fire Detection on Embedded Systems

*[1]Abubakar Hassan and [1] Abdulkadir I. Audu
[1]Department of Computer Engineering, University of Maiduguri, Maiduguri, Nigeria
abubakarhassan@unimaid.edu.ng| lm324fairchild@yahoo.com m

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ORIGINAL RESEARCH

Abstract— Existing fire detection systems are generally sensor-based. Such traditional sensor-based systems have limited detection range, slow response, high false alarm and inability to give rich descriptive information. To overcome these shortcomings, computer vision-based methods for fire detection have been proposed. These vision-based systems have advantages of faster response, larger surveillance coverage, affordable cost and less human interference. However, the performance of such systems is affected by the complexity of scene under observation, irregular lighting and low-quality frames. The limitations of both traditional sensor-based and vision-based systems for fire detection can be addressed by using convolutional neural network (CNN). Despite their superior performance in various computer vision tasks, computational complexity of CNN models remain a key concern for deployment on embedded platforms which are characterised by limited resources and memory. This paper presents a computationally less expensive CNN model for fire detection that can be easily deployed on embedded hardware platforms such as FPGA. SqueezeNet, a pre-trained CNN model on ImageNet dataset, was modified and trained using transfer learning approach to classify fire images. SqueezeNet is a computationally less intensive CNN architecture which is 18 layer deep and 5.2 MB in size that makes it a good choice for embedded applications. It yielded an accuracy of 95% on the benchmark dataset which is better than state-of-the-art feature-based approaches. But the performance of the model can still be enhanced through further experimentation by considering a larger dataset.

Keywords— Computer Vision, Convolutional Neural Network, Deep Learning, Embedded Systems, Fire Detection.

1 INTRODUCTION

Fire has a vital role in human society. It is used for a host of domestic and industrial applications such as cooking, and blacksmith by human beings. Despite its huge benefits, fire can be disastrous if left unchecked. Such fire is a great danger to human lives, infrastructure and the environment. Fire outbreaks cause huge human casualties and massive property damage(Rabiu, 2022). Most fire detection in use today are sensor-based. They measure ultraviolet or infrared radiation, heat, gas or particulate emissions generated by fire. Such sensor-based systems have shortcomings of limited detection range, transport delay, high false alarm and lack of capability to give additional information on location, growth rate, and size of fire (Khan et al., 2019; Rabiu, 2022; Xang et al., 2020). With rapid advances in digital camera technology, computer vision and artificial intelligence techniques, vision-based methods for fire detection have been proposed to address the limitation of the sensor-based system. These vision-based systems have advantages of larger coverage area, faster response, affordable cost and less human interference (Hassan et al., 2024). However, the performance of these systems is affected by the complexity of scene under observation, irregular lightning and low-quality frames. In recent years, Convolutional Neural Network (CNN) have been proposed to address the limitations of the vision-based systems for fire detection (Hassan & Audu, 2022; Mukhopadhyay et al., 2019).

Despite their excellent results in many image processing and computer vision tasks, computational complexity remains a key concern for deployment of CNN models on embedded platforms which are characterised by limited resources and memory(Onova & Omotehinwa, 2021; Sobowale et al., 2024). In this work, fire image detection model based on lightweight convolutional neural network is proposed targeting deployment on embedded computing hardware platform. SqueezeNet is a computationally less intensive CNN architecture which is 18 layer deep and 5.2 MB in size that would be a great candidate for embedded system deployment. The transfer learning approach to deep learning was used to fine-tune and train CNN architecture of SqueezeNet for fire image classification. The remaining part of the paper is organized as follows. Session 2 provides a review of related works. Section 3 presents the materials and method used. The result and discussion is provided in section 4 and finally section 5 concludes the paper.

2 RELATED WORKS

Tao, Wang and Zhang (2016) proposed an innovative method based convolutional neural network that can be trained end to end from raw image pixel values to classifier outputs and segment automatically features in a way to avoid the tedious image preprocessing stage of the hand-engineered feature-based methods. Experiment results obtained show the proposed method has high detection accuracy rates with low false alarm rates on the small dataset that clearly achieves greater performance compared to the existing methods. However, the method is computationally intensive which makes it not suitable

*Corresponding Author abubakarhassan@unimaid.edu.ng

Section B- ELECTRICAL/COMPUTER ENGINEERING & RELATED SCIENCES
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for embedded systems deployment.

Another research study by Son et al., (2018) proposed a method for fire detection based on deep learning. The deep learning networks employed were Alex Net, Google Net and VGG-16 in three manners. Image input that was captured by surveillance camera is classified into three different categories: normal, smoke and flame. Then, the network is trained to detect each corresponding category. The results obtained illustrate that all the three network models were able to recognize fire at over ninety percent detection accuracy. Despite this, the approach is computationally complex which limits its deployment on embedded architecture such as FPGA.

An enhanced object detection method based on deep convolutional neural network for fire detection was proposed. Firstly, the feature extractor is substituted in various neural network object detectors for faster R-CNN, Single Shot MultiBox Detector (SSD), Region based fully Convolutional Networks(R-FCN). Secondly, the MSCOCO dataset was used to optimize the parameters of the object algorithm. Lastly, the smoke detection dataset was used to perform the experiments. The proposed algorithm achieved great results in terms of accuracy and computational speed compared with the existing smoke detection methods (Zeng et al., 2018) . But it is computationally expensive to be deployed on resources-constrained platforms such as FPGA.

Researchers in (Muhammad et al., 2018) proposed a cost-effective CNN for fire detection in surveillance videos. The model is inspired from Google Net architecture which is reasonably less computationally complex and suited for the intended task compared to other networks that have high computational cost such as Alex Net. Taking into consideration the nature of the target task and fire data, the model is fine tuned to achieve balance between efficiency and accuracy. Results obtained using benchmark fire datasets show that the proposed model was effective and suited for fire detection based on video images captured by cameras from surveillance systems in comparison to the state-of –the art methods. However, the model is tested on very few images.

An algorithm based on convolutional neural network for video-based flame detection was proposed. First, the video image is extracted RGB-HIS colour synthesis model and enhanced adaptive mixture Gaussian model. Then, the classifier is designed by learning a great number of fire dataset using the CNN designed. Then, the flame region of interest is extracted by the classifier criteria. The result obtained reveal that the proposed algorithm has high detection accuracy (Hao, Linhu and Weixin, 2019). Despite this, the algorithm is computationally complex and cannot be suitable for deployment on embedded architecture such as FPGA.

In (Wang et al., 2019), presented a method for video-based smoke detection that combines conventional smoke detection and a lightweight convolutional neural network. First, the smoke YUV colour space information is fused to minimize the smoke region of interest based on the VIBE algorithm. Secondly, the lightweight convolutional neural network is designed to segment the information on smoke image in an automatic manner. The training speed of the model is enhanced by using the transfer learning approach for deep learning. The proposed method achieves the real-time performance of smoke detection, guarantees the accuracy of smoke detection and minimize the false positive level. However, the accuracy of the model can be improved for better detection performance

Authors in (Shi, Lu and Cui, 2019) developed a method that combines dark channel image input and a relative precise convolutional neural network (CNN). The difference between the smoke and background could be greatly enhanced by the dark channel of an image. The comparatively concise CNN could be efficiently trained on an insufficient dataset. Results from the experiment performed show extensively that the proposed method has achieved great performance compared to other smoke detection methods. But it is computationally expensive to be deployed on resources-constrained platforms such as FPGA.

The existing CNN based Methods for fire detection in video sequences was extended by integrating Multiple Instance Learning (MIL) in (Aktas et al., 2019). MIL ease the need for having accurate locations of fire patches in video frames, which are need for patch level CNN training. Only frame level labels showing the presence of fire somewhere in a video frame are required instead. Thus, reducing substantially the annotation and training efforts. The proposed approach is tested on a new fire dataset developed by extending some of the recently used fire datasets with video sequences obtained from the web. Result obtained illustrate that the presented method enhances fire detection performance. However, the method is computationally intensive which makes it not suitable for embedded systems deployment.

In the work of (Mukhopadhyay et al., 2019), a model was developed that has the capability of forecasting fire event with a reasonably great accuracy. The model is based on the convolutional neural network architecture, Mobile Net. The developed model can be deployed on embedded computing devices in an easy manner because it has small size and hence can also be employed as a robust stand-alone fire detection system. But the accuracy of the model can be enhanced for better performance.

Authors in (Saeed et al., 2020), a hybrid approach was presented that is consisted of an Adaboost MLP neural network model to forecast fire events. Subsequently, an Adaboost LBP model was developed to extract the region of interest (ROIs) and finally a convolutional neural network for fire detection with videos and images captured from installed surveillance camera. Despite this, the approach is computationally complex and cannot be suitable for deployment on embedded systems and platforms such as FPGA.

A method was proposed that employs the motion-flicker based dynamic features and deep static features for video-based fire detection. First, the dynamic features are segmented by analysing the differences in motion and flicker features between fire and non-fire objects in video scenes. Second, an adaptive lightweight convolutional neural network is proposed to segment the deep static features of fire. Finally, the dynamic and static features of fire are cascaded to develop a video-based fire detection system with enhanced efficiency in terms of accuracy and run time (Xie et al., 2020). Despite this, very small dataset was considered.

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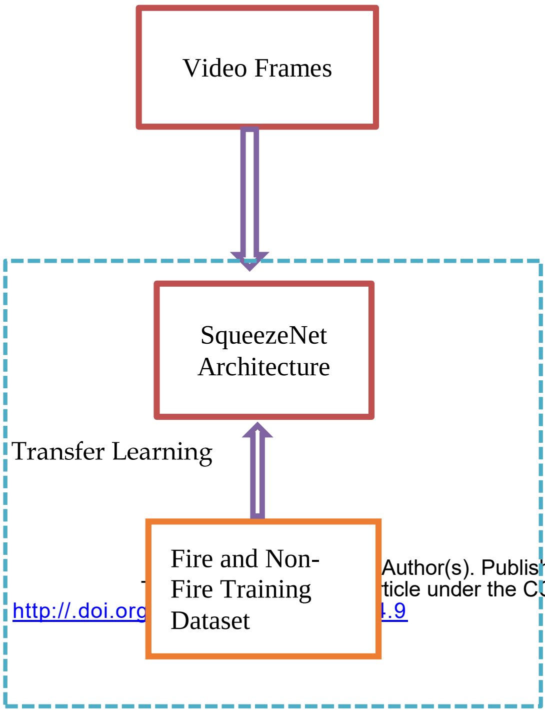
A robust fire detection system based on two-dimensional convolutional neural network where an object tracker is integrated into an object detector with the aim of confirming if detected events show fire or smoke behavior over time (Vinicius et al., 2021) . However, the approach is computationally complex and cannot be deployed on embedded systems.
Zhang et al., (2021) developed an effective asymmetric encoder-decoder U-shape architecture based on Squeeze Net, Attention U-Net and Squeeze Net, performs most of the time as an extractor and a discriminator of forest fire. The model uses attention mechanism to extract useful features and suppress non-related features by embedding Attention Gate (AG) units in the skip connection of U-shape structure. Key features are highlighted through this way in order to that the proposed method may be great at forest fire extraction problems with a minimum set of parameters. However, the method is computationally intensive which makes it not suitable for embedded systems deployment.
Researchers in (Majid et al., 2022) presented an attention based convolutional neural network model for fire detection using real life images. An attention mechanism was also added to the model which achieved great improvement in the performance of data. The introduced neural network has demonstrated significantly great performance on the testing dataset having minimal false positive level. However, the method is computationally intensive which makes it not suitable for embedded systems deployment.
It is evidently clear that many CNN models have been proposed to address the limitations of feature-based approaches to computer vision-based fire detection in the literature. However, computational complexity remains a key concern which restricts the deployment of these CNN models, despite their superior performance, on embedded computing platforms such as FPGA. As a result, this paper proposed a computationally less intensive CNN model for vision-based fire detection on embedded architecture.

3 MATERIALS AND METHOD

The flow chart of the fire detection model is shown in Figure 1.



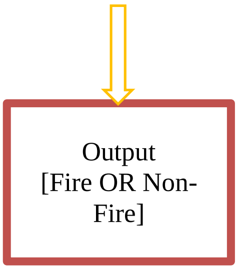


Fig 1. Flow Chart of the Fire Detection Model

3.1 Dataset Description

The modified SqueezeNet architecture was trained and tested using 5258 fire images and 5061 non-fire images obtained by (Muhammad et al., 2019). The segregation has been achieved in the following percentages:20% of the total image is used for testing, 20% have been used for validation and the remaining 60% comprises the training set.

3.2 Convolutional Neural Network

CNN is a deep learning architecture which is inspired by the biological structure of a visual cortex. It is a class of deep feed-forward artificial neural networks that are widely used to classify images.
A CNN architecture consists of three (3) main layers stacked in order.

1. The convolution
2. Pooling
3. Fully Connected

In convolution layer, several kernels of different sizes are used on the input data to generate feature maps. These feature maps are input to the next operation of pooling where maximum activations are selected from them within small neighbourhood. These operations are vital for reducing the dimension of feature vectors and for achieving spatial invariance up to a certain degree. Another important layer of the CNN architecture is fully connected layer, where high-level abstractions are modelled from the input data. The convolution and fully connected layers contain neurons whose weights are learnt and adjusted for better representation of the input data during training process.
The transfer learning approach was used to modify SqueezeNet (a pre-trained CNN architecture on ImageNet dataset) to the classes of our dataset. SqueezeNet is a convolutional neural network that is 18 layers deep and 5.2 MB in size. Figure 2 illustrates the schematic diagram of the SqueezeNet Architecture.

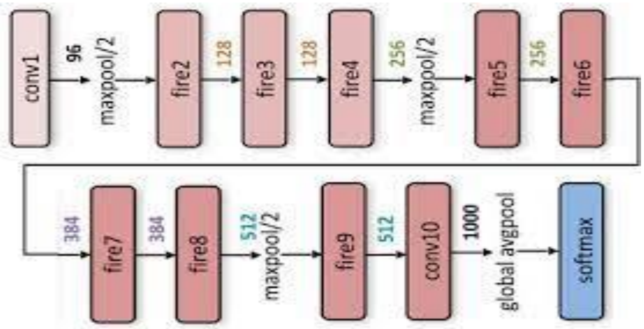


Fig 2. Schematic Diagram of the SqueezeNet.

3.3 The squeezeNet Model Training

All the experiments were performed on Corei3 8GB RAM Computer using MATLAB R2021 Deep Learning Toolbox. The original pre-trained SqueezeNet architecture was modified as follows: The last learnable layer which is the convolutional layer (1000 classes) was replaced with a convolutional layer with the number of filters was equal to two (2) nodes (fire and non-fire). The output layer was replaced with new a new layer. We set the initial learn rate to 0.0001, validation frequency to 5, max epochs to 8 and mini batch size to 11. It achieved accuracy of 95% on our test datasets.

4 RESULTS AND DISCUSSION

In this section, the experimental result of the model performance on the test set is presented. Four evaluation metrics were used including Accuracy, Precision, Recall, F1 score which are computed as follows.

$$\text{Accuracy} = (TP + TN)/ (TP + TN + FP + FN) \quad (1)$$

$$\text{Precision} = TP/ (TP + FP) \quad (2)$$

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

$$F1 = (2 \times \text{Precision} \times \text{Recall})/ (\text{Precision} + \text{Recall}) \quad (4)$$

Where TP is the true positive which is defined as number of images in which fire was correctly detected. FN is the false negative which indicates the number of images in which non-fire situation is predicted as non-fire. TN denotes true negative which shows the number of images in which non-fire objects or situation are detected as fire. FP represents false negative which shows the number of images in which fire is incorrectly identified

Accuracy is defined as the ratio of correctly classified images to the total number of images. The modified model has an accuracy of 0.95.

Precision is defined as the ratio of actual true cases to detected true cases. Precision of the modified model is 0.96.

Recall is the ratio of true positives to that of the sum of all cases that were positives. This is the sum of true positives and false negatives which indicates how much of the positives are correctly identified. The recall for the modified model is 0.899.

The F measure is the harmonic mean of precision and recall. It is employed to identify both precision and recall in one metric.

Table 1 gives a summary result of the CNN model on the test dataset. The results show that the model proposed in this paper can effectively detect fire in video images. The samples of the test result by modified SqueezeNet is illustrated in Figure 3. It shows that the model performed well under low-light conditions and complex scene environment.

Table 1. Test Result Summary of the Model

Accuracy	Precision	Recall	F1
95.0%	96.0%	89.9%	93.0%

Fig 3. Samples of the Test Results

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5 Conclusion

A computationally less intensive CNN model for fire image detection suitable for deployment on embedded platforms is presented. The transfer learning approach to deep learning was used to fine-tune and train SqueezeNet model for fire image classification using MATLAB R2021b environment. The model achieved an accuracy of 95.0% on the test dataset. The test results show that the modified CNN model can effectively detect fire in video images and has good application value for deployment on embedded computing system due to its computational size. However, the accuracy and the false alarm can be further enhanced by further experimentation by considering a larger dataset.

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References

Aktas, M., Bayramcavus, A., & Akgun, T. (2019). Multiple instance learning for CNN based fire detection and localization. *2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance, AVSS 2019*, *December*. https://doi.org/10.1109/AVSS.2019.8909842

Hao, X., Linhu, C., & Weixin, H. (2019). *Video Flame Detection Using Convolutional Neural Networks*. 539–543.

Hassan, A., & Audu, A. I. (2022). TRADITIONAL SENSOR-BASED AND COMPUTER VISION-BASED FIRE DETECTION SYSTEMS: A REVIEW. *Arid Zone Journal of Engineering , Technology and Environment(AZOJETE)*, *18*(3), 469–492. www.azojete.com.ng

Hassan, A., Umerah Ngene, C., & Yusuf Dibal, P. (2024). PERFORMANCE EVALUATION OF FPGA ACCELERATOR FOR VISION BASED FIRE DETECTION SYSTEM. *BAYERO JOURNAL OF ENGINEERING AND TECHNOLOGY*, *19*(2).

Khan, M. N. A., Tanveer, T., Khurshid, K., Zaki, H., & Zaidi, S. S. I. (2019). Fire detection system using raspberry pi. *2019 International Conference on Information Science and Communication Technology, ICISCT 2019*, 1–6. https://doi.org/10.1109/CISCT.2019.8777414

Majid, S., Alenezi, F., Masood, S., Ahmad, M., Gündüz, E. S., & Polat, K. (2022). Attention based CNN model for fire detection and localization in real-world images. *Expert Systems with Applications*, *189*(October), 116114. https://doi.org/10.1016/j.eswa.2021.116114

Muhammad, K., Ahmad, J., Mehmood, I., Rho, S., & Baik, S. W. (2018). Convolutional Neural Networks Based Fire Detection in Surveillance Videos. *IEEE Access*, *6*, 18174–18183. https://doi.org/10.1109/ACCESS.2018.2812835

Muhammad, K., Ahmad, J., Member, S., Lv, Z., & Bellavista, P. (2019). *Efficient Deep CNN-Based Fire Detection and Localization in Video Surveillance Applications*.

Mukhopadhyay, D., Lyer, R., Kadam, S., & Koli, R. (2019). *PGA Deployable Fire Detection Model for Real- Time Video Surveillance Systems Using Convolutional Neural Networks*. 1–8.

Onova, C. U., & Omotehinwa, T. O. (2021). Development of a Machine Learning Model for Image-based Email Spam Detection. *FUOYE*

Journal of Engineering and Technology, *6*(4). https://doi.org/10.46792/fuoyejet.v6i4.718

Rabiu, H. (2022). *Robust Fire Detection Algorithm using Color and Shape Information Habibu Rabiu*. *17*(1), 22–29.

Saeed, F., Paul, A., Karthigaikumar, P., & Nayyar, A. (2020). Convolutional neural network based early fire detection. *Multimedia Tools and Applications*, *79*(13–14), 9083–9099. https://doi.org/10.1007/s11042-019-07785-w

Shi, X., Lu, N., & Cui, Z. (2019). *Smoke Detection Based on Dark Channel and Convolutional Neural Networks*. 23–28.

Sobowale, A., Abdul-Hameed, T., Sobowale, P., & Ogunleye, A. (2024). Reducing Road Mishaps: A CNN Model for Driver Fatigue Detection. *FUOYE Journal of Engineering and Technology*, *9*(1), 56–61. https://doi.org/10.4314/fuoyejet.v9i1.9

Son, G. young, Jang-Sik, P., Yoon, B.-W., & Song, J.-G. (2018). *Video Based Smoke and Flame Detection Using Convolutional Neural Network*. 365–368. https://doi.org/10.1109/SITIS.2018.00063

Tao, C., Wang, P., & Zhang, jian. (2016). *Smoke Detection Based on Deep Convolutional Neural Networks*. 54–57. https://doi.org/10.1109/ICIICII.2016.68

Vinicius, P., Venancioˆ, A. B. De, Rezende, M. T., Lisboa, C. A., & Barbosa, V. A. (2021). *Fire Detection based on a Two-Dimensional Convolutional Neural Network and Temporal Analysis*. *November*.

Wang, X., Zhou, H., Arnott, W. P., Meyer, M. E., Taylor, S., Firouzkouhi, H., Moosmüller, H., Chow, J. C., & Watson, J. G. (2020). Evaluation of gas and particle sensors for detecting spacecraft-relevant fire emissions. *Fire Safety Journal*, *113*(March), 102977. https://doi.org/10.1016/j.firesaf.2020.102977

Wang, Y., Cheng, J., & Liu, T. (2019). *Smoke video detection based on lightweight convolutional neural network*. 1462–1466.

Xie, Y., Zhu, J., Cao, Y., Zhang, Y., Feng, D., Zhang, Y., & Chen, M. (2020). Efficient video fire detection exploiting motion-flicker-based dynamic features and deep static features. *IEEE Access*, *8*, 81904–81917. https://doi.org/10.1109/ACCESS.2020.2991338

Zeng, J., Lin, Z., Qi, C., Zhao, X., & Wang, F. A. N. (2018). *AN IMPROVED OBJECT DETECTION METHOD BASED ON DEEP CONVOLUTION NEURAL NETWORK FOR SMOKE DETECTION*.

Zhang, J., Zhu, H., Wang, P., & Ling, X. (2021). ATT Squeeze U-Net: A Lightweight Network for Forest Fire Detection and Recognition. *IEEE Access*, *9*, 10858–10870. https://doi.org/10.1109/ACCESS.2021.3050628

