

Convolutional Neural Network based Fire Detection for Surveillance Environment

Pooja Verma¹ and Rajitha B²
¹⁻²MNNIT Allahabad/CSE, Prayagraj, India
Email: poojaverma@mnnit.ac.in, rajitha@mnnit.ac.in

Abstract—Considering the severity and the loss occurred by the types of damage that can occur due to fire disaster, there is always a demand of continuous progression in fire detection capabilities. This paper proposes fire detection model using Convolution neural networks inspired from ShuffleNet. Usually it has been observed a trade-off between model's performance and its size, restricting its deployment on memory constrained devices. In this paper we have attempt to achieve descent accuracy which is comparable to some existing work without compromising on its model size. Experimental results on benchmark dataset verify its accuracy and justify its applicability for effective fire disaster management on small portable devices with limited memory.

Index Terms— Convolutional neural networks, fire detection, ShuffleNet.

I. INTRODUCTION

Fire disaster can be life threatening for the humans on the earth and the wild species inhabited by the forest leading to ecological and economical damage. Each year wildfires have caused the annihilation of very large area of land [1] and over 200,000 forest fires happen per annum within the world. Forest fires burned in total area of 3.5 to 4.5 million km² [2]. According to the 2015 NFPA report, a total of 1345500 fires transpired in US alone, resulted in \$14.3 billion loss, 15700 civil fire injuries, and 3280 civilian deaths. Also among the total deaths caused by fire, 78% were those which happened because of home fires [3]. Early fire detection can help in facilitating quick response which will also be helpful in saving lives and mitigating fire caused damage.

In past among existing and deployed fire alert system many were photoelectric based smoke detectors that can perform good in only closed environments as they need close proximity to fire and which are thermal detectors based may require sufficient level of fire which can cause delay in detection and by the time it detects it would have become raging fire and hence, uncontrollable.

Because of recent developments in technology, smarter surveillance environment can be developed consisting of embedded visual sensors with processing capabilities, which can perform better in open as well as closed environments and in addition to this they can also provide useful information such as location of the affected area, scale up to fire has reached and monitor larger area which requires no human intervention for fire confirmation.

A. Related work

There do already exist numerous algorithms and methods proposed by various researchers in the past for fire detection. Chen et al. [5] for fire detection have used the dynamic property and irregularities of flames in both

RGB and HIS color spaces. Foggia et al. [6] proposed a multi-expert framework in which they combined color, motion and shape variation properties, for flame detection in video surveillance. Patel et al. [7] proposed technique comprising the fusion of color cue and flicker features. Borges and Izquierdo [8] proposed a framework consisting of color, area size, coarseness of surface, roughness, skewness features and Bayes classifier for fire recognition. Yan *et al.* [9] extracted multiple static and dynamic features such as color, texture, area, and shape for forest fire recognition. Marbach et al. [10] utilized motion information to investigate the YUV color space for the classification of pixels into fire and non fire regions. To overcome the problem of false alarms when using only color or motion features for fire detection, Töreyn et al. [11] utilized temporal and spatial wavelet analysis but their approach restricts its usage in real world scenario as it uses many heuristic thresholds. Rafiee et al. [12] used the static and dynamic properties like motion and disorder characteristics of the fire and smoke. But the false negative rate remains an issue here also due to the presence of other objects with similar color properties as the fire pixels. Despite combining the chromatic as well as dynamic properties of the fire by the Rinsurongkawong et al. [13], their method failed in the presence of fire like objects in the background.

Hence, in the presence of fire color object in the image or because of the lightning and shadow, the color based methods may sometimes result in less accurate fire detection model.

But now in recent years as incomparable results have been achieved for various tasks in computer vision field using deep learning approach. Zhang et al. [14] utilized local fire patch detection with fine-tuned pre-trained CNN, 'AlexNet' [15]. Different variants of CNN models were fine tuned by Muhammad et al. AlexNet [16], SqueezeNet [17], GoogleNet [18], and MobileNetV2 [19] while Sharma et al. [20] used VGG16 [21] and Resnet50 [22] as baseline models for fire detection. Deep learning based models may sometimes result in large on-disk size restricting their usage in small embedded devices.

Thus it can be said that for prevention of fires and to avoid their growth a monitoring system can be useful as it will provide 24/7 monitoring without interruption which in turn will also reduce the labor costs which is economically efficient.

II. THE PROPOSED FRAMEWORK

The issues with the traditional features extraction methods for fire detection is extraction of hand engineered features which is a tedious task, when the dataset consist of large number of images and most of the time when methods are based on limited set of features, it results in their low performance in terms of accuracy. To encounter this CNN framework has been explored to avoid feature engineering manually which can be tedious and time consuming process, on the other hand CNN can also learn rich features from raw fire data automatically. This paper presents a CNN framework inspired from the transfer learning strategies for fire detection. We have trained as well as fine tuned a ShuffleNet [4] model as per our task.

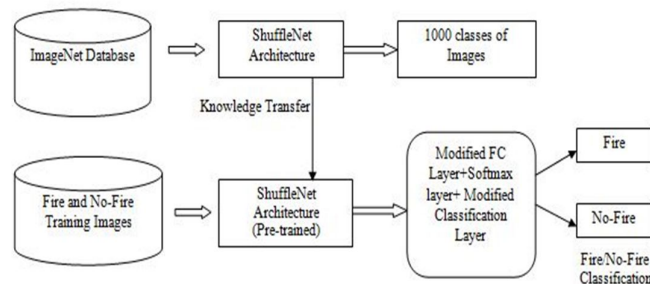


Fig. 1. Framework for Fire detection using Transfer learning approach

A. Convolutional Neural Networks

Convolutional neural network is one among the most popular architectures for deep learning which has wide application in image or object recognition and classification. They have exhibited promising results in a variety of tasks such as image classification, localization, and image segmentation. Generally CNN consists of several layers such as convolutional layers, pooling layers, fully connected layers and classification layer although there can be more additional layers different from the mentioned here. CNNs that usually consist of convolution layer in which input data are taken through several convolutional filters, each of which are applied to generate feature maps. Output of the previous layer are input to the next layer pooling which is used for output simplification by downsampling and is salient for translation invariance. The next to last is a Fully connected layer whose output

is vector of m dimensions containing the probabilities of each class, that the network are going to be ready to predict. The final layer of CNNs is classification layer.

B. Fire detection using CNNs

For our intended fire classification problem we have used CNN for generating features for fire detection task as it can be time consuming when the dataset is usually large if feature extraction is done manually.

C. Shufflenet

ShuffleNet [4] is a particularly efficient convolution model designed for smart phones. We have used a model ShuffleNet with few amendments and fine tuning as per our problem. ShuffleNet is a convolutional neural network (CNN) which is primarily built from Shufflenet units. It has been trained on millions of images from the ImageNet database [23]. ShuffleNet unit consists of a 1×1 point-wise group convolution layer followed by channel shuffle. The advantage of pointwise group convolutions is that it helps in reducing the computational complexity usually consumed by 1×1 convolutions and channel shuffle helps in orderly disruption of channels of each feature map to get rid of “poor information flow” problem caused by group convolution. In other words, it creates an association among the input channel and output channels. This architecture consist of 172 layers with convolutions, max pooling, average pooling, channel shuffling layers i.e. it contains 3 stages which have repetitions as 3, 7, 3. So, in accordance to our fire detection task we have changed the no. of outputs of last fully connected layer and of classification layer as the numbers of classes are 2 one is fire class and the other is no-fire class.

One of the major reason behind choosing the ShuffleNet compared to other CNN models in this work is its classification accuracy, smaller size along with its sustainability of implementation on common mobile platforms such as smart phones, drones and FPGAs.

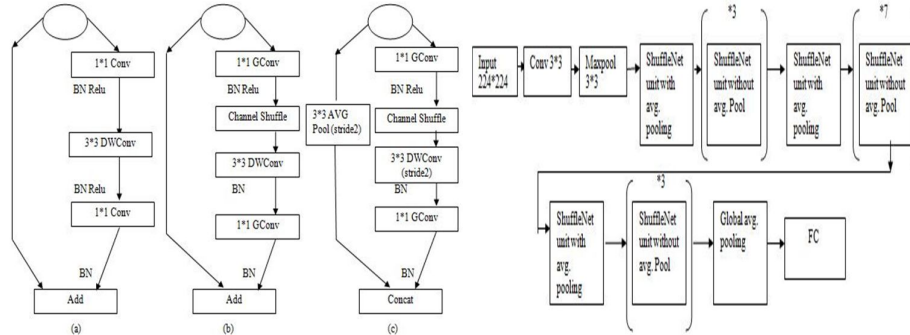


Fig.2.ShuffleNet Units[4] a)Bottleneck unit[30] with depthwise convolution(DWConv) [31,26] ; b)ShuffleNet unit with point wise group convolution;c)ShuffleNet unit with stride=2

Fig.3. ShuffleNet architecture

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Dataset Description

In this experiment we have used the concept of transfer learning where we use already pre-trained network and fine tune it according to our specific task as it saves our time when compared to the network trained from scratch. When the dataset is small, the model performance on the training dataset may be good but the results on the test data set can be unsatisfactory. Using transfer learning this problem can be alleviated.

For training the network we have used the images from the dataset provided by the [24] which initially consist of 1124 fire images and 1301 no fire images which they have sampled from well known datasets, and few are collected from Internet as mentioned by them in their paper. Also the dataset prepared by them is only used here for training and validation. But in our work we have taken equal no. of images i.e.912 for each, which are randomly picked from the training dataset. Also we have used 80% and 20% split between the training and validation set.

For testing and the verification the fine tuned network inspired from ShuffleNet we have used the very challenging benchmark dataset [25] containing 226 images in which 119 are fire images and 107 without fire images.



Fig.4. Images from the training dataset¹ [24] (a) is the fire image in which fire is inside the room (b) it is showing the fire in daylight where house is burning (c) is the night time image in which house is burning and (d) is the no fire daytime image where sunlight is there (e) is the sunset image which is looking similar to fire (f) is the daytime image where the sunlight is falling only on the smaller region in the image



Fig.5. Fire from the test dataset [25] (a) is the fire image where people are also standing there (b) is the night time fire image consisting of fire (c) is the fire image with one person standing near it and (d) is sunset image which is almost resembling of fire (e) is the sunset image where the orange-yellow sky is reflecting in the water also (f) is the no fire image where the sunlight is falling inside a room

The dataset [25] despite of its size is extremely challenging as it contains fire colored objects, sunrise and sunset scenes which makes the fire detection task difficult. The results are compared with the hand crafted features as well as deep learning based methods. Also to evaluate the performance of the network with different no. of mini batch size has been experimented i.e. with 16, 32 and 64.

B. Results

TABLE I. TRAINING HYPERPARAMETERS

Initial Learning Rate	Mini-Batch Size	Epochs
0.001	16,32,64	10

Table II below illustrates the different testing accuracy achieved while training for 10 epochs and with different no. of minibatch size 16, 32 and 64.

Table 3 compares the false positive rates, false negative rates and accuracy achieved on the benchmark dataset by our method and the other methods mentioned by the author in [29].

¹Online available at <https://github.com/arpit-jadon/FireNet-LightWeightNetwork-for-Fire-Detection>, [Accessed: July, 2019]

TABLE II. ACCURACY COMPARISON OF THE MODEL ON TEST DATASET WHEN TRAINED FOR DIFEERENT BATCH SIZE

MiniBatch Size for Fine tuned Shuffle Net	False Positive Rate (%)	False Negative Rate (%)	Accuracy (%)
16	9.3	15.1	87.6
32	12.1	10.9	88.5
64	11.2	24.4	81.9

TABLE III. COMPARISON OF PROPOSED WITH OTHER EXISTING FIRE DETECTION METHODS

Technique	False Positive Rate (%)	False Negative Rate (%)	Accuracy (%)
ShuffleNet after fine tuning with minibatch size 32	12.1	10.9	88.5
ShuffleNet[29]	21.50	10.92	84.07
MobileNet[29]	23.36	12.61	82.30

Unlike metrics mentioned in Table 3, we have calculated (precision, recall and F-measure) for evaluating performance from different perspective in Table 4 below:

TABLE IV. COMPARISON OF PROPOSED WITH OTHER EXISTING FIRE DETECTION METHODS

Technique	Precision	Recall	F-Measure
ShuffleNet after fine tuning batch size 16	0.91	0.84	0.87
Muhammad et al.[18]	0.80	0.93	0.86
Muhammad et al.[27]	0.82	0.98	0.89
Bowfire[25]	0.51	0.65	0.57
[28]	0.63	0.45	0.52

IV. CONCLUSIONS

The recent advancement in the processing capabilities of visual sensors has enabled the task of surveillance easier without manual intervention to avoid abnormal events such as fire which can result in great loss and economic damage. This paper presents a CNN based fire detection model inspired from ShuffleNet architecture which has been trained on well known ImageNet dataset. So here in this work fire detection model has been proposed which helped in achieving an accuracy of 97.53% on the validation dataset when mini batch size was 32 and 88.5% on benchmark dataset[25].

REFERENCES

- [1] J. R. Martinez-de Dios, B. C. Arrue, A. Ollero, L. Merino, and F. Gómez-Rodríguez, "Computer vision techniques for forest fire perception," *Image and Vision Computing*, vol. 26, pp.550–562, 2008.
- [2] Y. Meng, Y. Deng, and P. Shi, "Mapping Forest Wildfire Risk of the World," in *World Atlas of Natural Disaster Risk*, P. Shi and R. Kaspersen, Eds., pp. 261–275, Springer Berlin Heidelberg, Berlin, Germany, 2015.
- [3] H. Haynes. (2016). *Fire Loss in the United States During 2015*. [Online]. Available: <http://www.nfpa.org/>
- [4] X. Zhang, X. Zhou, M. Lin, and J. Sun, "ShuffleNet: An extremely efficient convolutional neural network for mobile devices," in *Proc. IEEE/CVF Conf. Computer. Vis. Pattern Recognition.*, pp. 6848_6856, Jun. 2018.
- [5] T.-H. Chen, P.-H. Wu, and Y.-C. Chiou, "An early fire-detection method based on image processing," in *Proc. Int. Conf. Image Process. (ICIP)*, Oct. 2004, pp. 1707_1710.
- [6] P. Foggia, A. Saggese, and M. Vento, "Real-time fire detection for video surveillance applications using a combination of experts based on color, shape, and motion," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 25, no. 9, pp. 1545_1556, Sep. 2015.
- [7] R. Patel, K. Mandaliya, P. Shelar, R. Savani, and C. I. Patel, "Automatic fire detection using combination of color cue and flame flicker," in *Proceedings of the International Conference on Intelligent Systems and Signal Processing*, pp. 25–33, Gujarat, India, March 2018.
- [8] P. V. K. Borges and E. Izquierdo, "A Probabilistic approach for vision-based fire detection in videos," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 20, no. 5, pp. 721_731, May 2010.
- [9] Y. Qiang, B. Pei, and J. Zhao, "Forest fire image intelligent recognition based on the neural network," *J. Multimedia*, vol. 9, no. 3, pp. 449_455, 2014.
- [10] G. Marbach, M. Loepfe, and T. Brupbacher, "An image processing technique for fire detection in video images," *Fire Safety J.*, vol. 41, no. 4, pp. 285–289, 2006.
- [11] B. U. Töreyn, Y. Dedeoğlu, U. Gündükbay, and A. E. Çetin, "Computer vision based method for real-time fire and flame detection," *Pattern Recognit. Lett.*, vol. 27, no. 1, pp. 49–58, 2006.
- [12] A. Rafiee, R. Dianat, M. Jamshidi, R. Tavakoli, and S. Abbaspour, "Fire and smoke detection using wavelet analysis and disorder characteristics," in *2011 3rd International Conference on Computer Research and Development*, vol. 3, pp. 262–265, IEEE, 2011.

- [13] S. Rinsurongkawong, M. Ekpanyapong, and M. N. Dailey, "Fire detection for early fire alarm based on optical flow video processing," in 9th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, pp. 1–4, IEEE, 2012.
- [14] Q. Zhang, J. Xu, L. Xu, and H. Guo, "Deep convolutional neural networks for forest fire detection," in 2016 International Forum on Management, Education and Information Technology Application, Atlantis Press, 2016.
- [15] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in neural information processing systems, pp. 1097–1105, 2012.
- [16] K. Muhammad, J. Ahmad, and S. W. Baik, "Early fire detection using convolutional neural networks during surveillance for effective disaster management," *Neurocomputing*, vol. 288, pp. 30–42, 2018.
- [17] K. Muhammad, J. Ahmad, Z. Lv, P. Bellavista, P. Yang, and S. W. Baik, "Efficient deep cnn-based fire detection and localization in video surveillance applications," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, no. 99, pp. 1–16, 2018.
- [18] K. Muhammad, J. Ahmad, I. Mehmood, S. Rho, and S. W. Baik, "Convolutional neural networks based fire detection in surveillance videos," *IEEE Access*, vol. 6, pp. 18174–18183, 2018.
- [19] K. Muhammad, S. Khan, M. Elhoseny, S. H. Ahmed, and S. W. Baik, "Efficient fire detection for uncertain surveillance environment," *IEEE Transactions on Industrial Informatics*, 2019.
- [20] J. Sharma, O.-C. Granmo, M. Goodwin, and J. T. Fidge, "Deep convolutional neural networks for fire detection in images," in International Conference on Engineering Applications of Neural Networks, pp. 183–193, Springer, 2017.
- [21] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 2014.
- [22] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770–778, 2016.
- [23] *ImageNet*. <http://www.image-net.org>
- [24] A. Jadon, M. Omama, A. Varshney, M. S. Ansari, and R. Sharma, "Firenet: A specialized lightweight fire & smoke detection model for real-time iot applications," *CoRR*, vol. abs/1905.11922, 2019. [Online]. Available: <http://arxiv.org/abs/1905.11922>
- [25] D. Y. T. Chino, L. P. S. Avalhais, J. F. Rodrigues, and A. J. M. Traina, "BoWFire: Detection of fire in still images by integrating pixel color and texture analysis," in *Proc. 28th SIBGRAPI Conf. Graph., Patterns Images*, Aug. 2015, pp. 95–102.
- [26] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "MobileNets: Efficient convolutional neural networks for mobile vision applications," 2017, *arXiv:1704.04861*. [Online]. Available: <http://arxiv.org/abs/1704.04861>
- [27] K. Muhammad, J. Ahmad, and S. W. Baik, "Early fire detection using convolutional neural networks during surveillance for effective disaster management," *Neurocomputing*, vol. 288, pp. 30–42, May 2018. [Online] Available: <https://www.sciencedirect.com/science/article/pii/S0925231217319203>.
- [28] S. Rudz, K. Chetehouna, A. Hafiane, H. Laurent, and O. Séro-Guillaume, "Investigation of a novel image segmentation method dedicated to forest fire applications," *Meas. Sci. Technol.*, vol. 24, no. 7, 2013, Art. no. 075403.
- [29] Y. Xie et al., "Efficient Video Fire Detection Exploiting Motion-Flicker-Based Dynamic Features and Deep Static Features," *IEEE Access*, vol. 8, pp. 81904–81917, 2020.
- [30] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 770–778, 2016.
- [31] F. Chollet. Xception: Deep learning with depthwise separable convolutions. arXiv preprint arXiv:1610.02357, 2016.