DeepFireNet - A Light-Weight Model for Fire-Smoke Classification

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Abstract-From the visual scenes detection of smoke and fire is a challenging task and many approaches have been proposed for the classification of smoke and fire images however an intelligent fire detection from an image is crucial to prevent large-scale fire events in the world also rule-based conventional algorithms are not very sufficient to perform these types of detections in real-world due to shape, size, color and texture of images. To improve the detection of fire and smoke detection we proposed a model named DeepFireNet that is an extension of the CNN model, DeepFireNet trained on the raw pixels of the images. Our proposed model can automatically extract features of images and for the robustness of our model, we have compared it with other models named AlexNet, Squeeze Net, and Fire Detection Model. We have achieved an accuracy of 92.33% with our proposed model on an open-source dataset. Furthermore, DeepFireNet is best in terms of memory usage because we have reduced the number of parameters and layers.

Data Availability: https://github.com/DeepQuestAI/Fire-SmokeDataset/releases/download/v1/FIRE-SMOKE-DATASET.zip

Keywords— Deep Learning, Convolutional Neural Network, Fire Detection, Smoke Detection

I. INTRODUCTION

To avoid large-scale damage, fire and smoke detection at an early stage is necessary. Several different tools and algorithms have been proposed for the detection of fire and smoke and in such traditional ways, mostly sensors are required. The main cons of these methods are that they can detect fire and smoke only near places where they are installed for detection purposes. Furthermore, these sensors cannot provide sufficient information about fire size location and direction.

To overcome the above imperfections many deep learning models have been proposed. These models can detect fire and smoke where these are installed. Chen et al [1] proposed a method for smoke detection. To conclude pixels that each pixel represents smoke or not, and diffusion & chromatically based rule used. Toreyin et al. [2] were used clue and motion features for the detection of fire and flame. Mueller et al. [3], propose a video-based optical flow method to detect fire and non-fire motion. To measure the dimensions of the flame GIS-based reality method was proposed by Bugarovich et al. [4].

The above-mentioned methods are used to create rule-based algorithms that depend on expert knowledge. The huge diversity can be found among features of fire and smoke due to color, texture and due to these diversities obtaining an effective accuracy is a challenging task.

To overcome the above issue of feature extraction, many deep learning algorithms are best to extract features of smoke and fire images. CNN is best to achieve an effective result in visual problems, only a few studies have been published with CNN in terms of fire and smoke detection. Two joined deep CNNs proposed by Zhang et al. [5] for detection of fire in image dataset. In this method firstly image is tested if the fire is detected in this image then other classifiers detect the exact location of a fire in the particular image.

Most of the proposed approaches are for detecting smoke and fire from images but as described above all they have some limitations. The advancements of computer vision and image processing techniques can be used to overcome problems faced in classification of fire and smoke problem. Video-based fire detection technologies can cover more areas for fire detection and fast responses. Deep neural networks perform very well concerning traditional algorithms. As described above CNN is the deep neural network for instance segmentation in machine learning and computer vision. In other words, it separates different objects in the image or video and returns classes around objects. The best approach of CNN is that it can automatically extract features from the fire and smoke image dataset. To train the model we have a dataset of images taken from different cameras from fire scenes and corresponding classes of the images which can very easily with the human eye as all the images are very clear to see smoke and fire.

II. BACKGROUND

In recent years, many methods are proposed for fire and smoke detection. Jian Zhang et al. [6] used Deep Convolutional Neural Network to take the advantages of neural networks to train the model for smoke detection. In this study 2D images and corresponding annotations used for training, the proposed method automatically extracts the features from the given image. The proposed method used the AlexNet model and change the output layers to 2 classes, one for smoke images and the second class for non-smoke images. In their proposed method total number of layers was 8 (5- convolutional layers), 4 sets of datasets were used for training and testing, and finally got the average accuracy alarm rate 99.56% and false alarm rate 44%.

Eric Moreau [7] proposed a method that used CNN which performs feature extraction and classification in the same architecture. CNN consists of different layers with a combination of convolutional layers and fully connected layers. They used a dropout rate of 0.5 to prevent the model from overfitting. In their dataset, they were considered simple 2D RGB images for training and testing for 3 classes (fire, smoke, and no-fire). The number of samples in the considered dataset was 1427 samples of fire images, 1758 smoke images samples, and 2399 negative images to train the model. After training, they achieved 97% accuracy on the testing dataset. They applied a sliding window of 12x12 on the last feature map to detect fire and smoke.

Angelo Genovese et al. [8] proposed an image processing system based on computational intelligence techniques for fire and smoke detection. Their proposed method provides an affordable system that consumes low power and minimum computational resources. As the smoke predicts the possibility of fire so they mainly focus on the detection of smoke to make this system responsive and affordable for low-cost platforms. The proposed method was designed to handle 320x240 images at the rate of 7 FPS, which makes it run faster. For the accomplishment of this task first, they performed feature extraction and then performs classification on two classes (fire, not fire). The feature extraction process mainly focuses on the below following things:

- Moving Region Detection
- Smoke Color Analysis
- Rising Region Detection
- Perimeter Disorder Analysis
- Growing Region Detection
- Perimeter Disorder Analysis

Finally, after training, they achieved a 1.97% True positive rate and 98% True negative rate on 7FPS.

Boyang Wan [9] proposed a method that based on deep normalization and convolutional neural network of 14 layers for automatic feature extraction and classification for fire and smoke detection from images. To improve the performance of traditional convolutional neural networks they replaced the convolutional layers with normalized convolutional neural layers. For the prevention of overfitting because of the imbalanced dataset, they generated more training samples from the original dataset by using intelligent image enhancement techniques in their study. They used a total of 10712 images for training from which 2254 images of fire and 8363 of non-fire. Finally, in their study, they achieved 97% True alarm rates and 60% false alarm rate.

Yong-Tae Lee et al. [10] proposed a method in which aerial images are considered for fire and smoke detection. In their study, they were considered unmanned vehicle images (UAV) due to the expensiveness of manned vehicles like aero planes in terms of fire monitoring, images taken from satellite can't be used for early fire detection due to low temporal resolution and low spatial resolution. For UAV images they used deep convolutional neural networks for wildfire detection. In their study, a total of 23053 images were used for training from which 10985 images were of 'fire' and 12068 images of 'non-fire'. Experiments on different convolutional neural networks performed for significant results achievements in terms of training time consumption, and out of them modified GoogLeNet they were able to achieve 99% accuracy for fire detection with 3 hours training time.

In this study, we have proposed a deep convolutional neural network model named DeepFireNet. The key points of our proposed model are, DeepFireNet can automatically extract the features from the images and makes automatic classification in a considered number of classes. A dataset that we have considered contains 2D images with corresponding classes (fire, smoke and neutral).

III. Convolutional Neural Network (CNN)

A convolutional neural network was first introduced by Fukushima [11] derived a hierarchical neural network inspired by Hubel's research work [12]. CNN is a deep learning algorithm that takes in an image as input and assigns importance such as weights/biases to different scenes or objects in the images. CNN performs automatic classification on given images. Mostly in other classification algorithms, we need some pre-processing techniques for better classification, but there is especially no need to pre-process the given image. CNN automatically performs features extraction from a given image and then automatically performs image classification in output classifiers layers in given classes.

A convolutional neural network consists of different types of layers to perform different tasks. Further details are given in the below following sections.

A. Convolutional Layers

Convolutional layers are the basic building blocks for Convolutional neural networks. Convolutional layers are the image convolution of the previous layers. The weights of the filters determine the convolutional filter. More number filters in a convolutional layer extract more features from the image and get details in more depth. We also specify the padding methods like 'zero paddings', 'the same padding' to control image border pixels.

B. Pooling Layers

Pooling layers subsample the input. We often perform pooling after each convolutional layer. There are different methods for performing pooling such as choosing maximum, linear combinations, or taking an average. The most commonly used pooling technique is MaxPooling (2x2) shown in Figure.1.

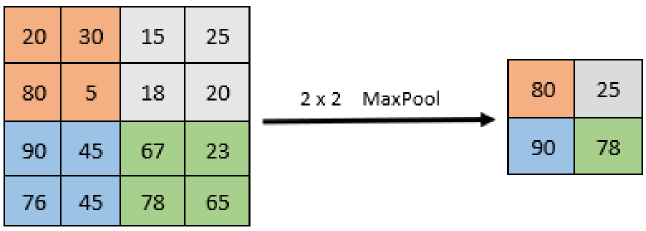

Figure 1:MaxPoolling(2x2)

C. Fully Connected Layers

Finally, after applying some convolutional and pooling layers, we used fully connected layers for high-level reasoning in the neural network. We specify the number of classes in the output layer that we required as output results.

In the neural network, every layer detects some specific features from the original data provided in the form of an image. Features detected by the first layer in the network can easily be recognized and interpreted. The features extracted by middle layers are difficult to recognize because of more abstract features. The last layer can classify the features selected from all previous layers in the network.

IV. Methodology

A. Dataset

Open-source dataset downloaded from DeepQuestAI GitHub repository and we have considered 3000 2D images for our DeepFireNet model and 100 images for each class used for testing (100*3), 900 images for each class used to train the model (900*3). The dataset contains images for the following classes.

- Fire

- Smoke
- Neutral

Figure 2: Smoke, Fire, Neutral

We have resized all images to 255*255. In this study, we were considered three classes and trained our model on three classes.

B. DeepFireNet Model Design

We have designed a DeepFireNet model in which there were total two convolutional layers with filters 32 and 64 are used to convolve image features automatically. As we know that overfitting is a common problem in deep learning based problems, to avoid overfitting we have used dropout of 0.3-0.5. To extract features in more depth we have to downsample the image, for this propose a MaxPooling layer is used. A flatten layer to create vector of features extracted from the image through convolutional layers, and then one fully connected layer is used with 64 number of filters. A rectified linear unit (ReLU) activation function is used in this model with all convolutional layers except the last layer. Finally the last fully connected layer is used with sigmoid function to obtain required output labels (fire, smoke, neutral). Figure 3 is the graphical representation of our proposed model.

The network is simple and the number of layers was less than other proposed models that our model is effective in terms of memory consumption and speed.

V. Experiments

A. Training & Accuracy

To train the DeepFireNet model, we use the system with 32GB RAM, 1TB disk drive, 3.2 GHz processor speed, CUDA 10.1 version with 12GB NVIDIA GPU. A batch size of 64 was used for training and testing, an Adam optimizer was used to optimize the loss weights to improve training performance, and the initial learning rate was set to 0.001. The number of epochs set to 200 for training and model weights were to be saved automatically after each epoch based on the increment in validation accuracy during training.

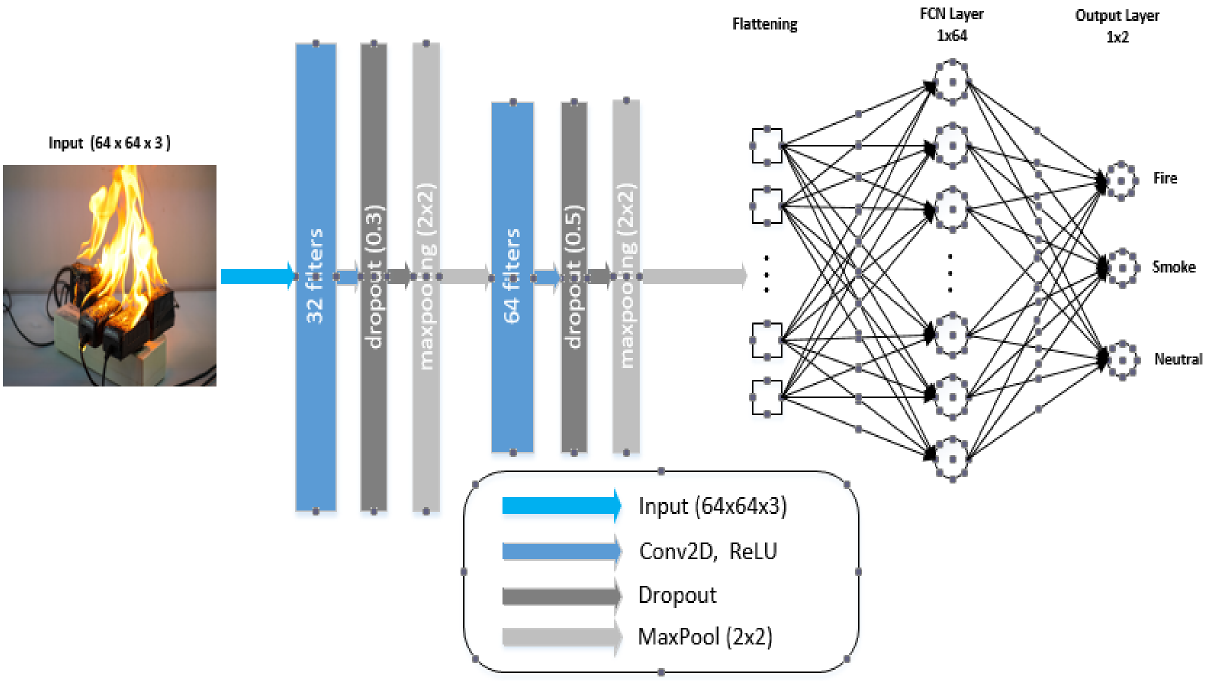

Figure 3: DeepFireNet Framework

Results achieved by our proposed model are represented in Figure 4. The validation score of our proposed model is 90±4.

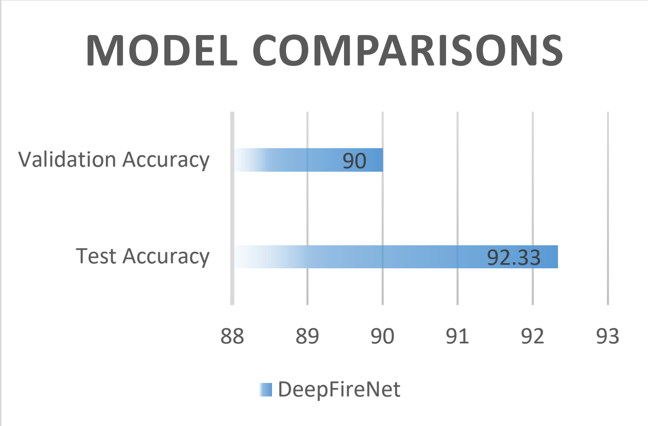

Figure 4: DeepFireNet Model Result

The accuracy and loss in terms of training and testing are displayed in Figure 5.

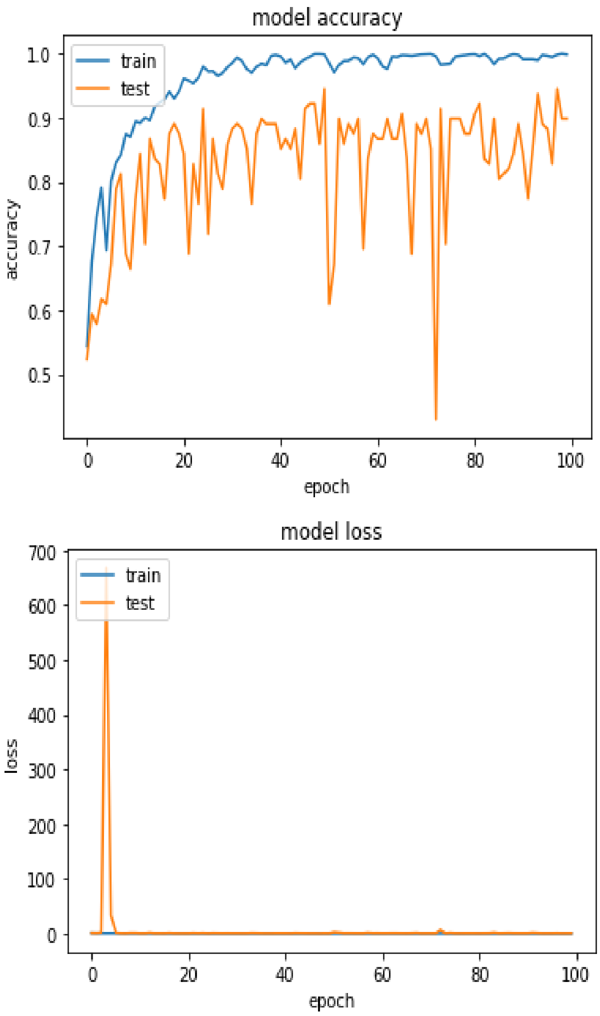

Figure 5: Accuracy and Loss for each CNN during training and testing performed on the Dataset

Figure 6 is represented confusion matrix of DeepFireNet model.

Truth data

Classifier results	Fire	Smoke	Neutral	Classification overall	User's accuracy (Precision)
Fire	94	5	1	100	94%
Smoke	4	86	10	100	86%
Neutral	2	1	97	100	97%
Truth overall	100	92	108	300	
Producer's accuracy (Recall)	94%	93.478%	89.815%		

Overall accuracy (OA): 92.333%

Kappa[1]: 0.885

Figure 6: DeepFireNet Confusion Matrix

B. DeepFireNet Robustness

For the robustness of our model, we have presented a detailed comparison of different fire detection models with our proposed DeepFireNet. Our proposed model achieved the highest accuracy than other pioneered models (Fire Detection, Squeeze Net, and AlexNet) [13].

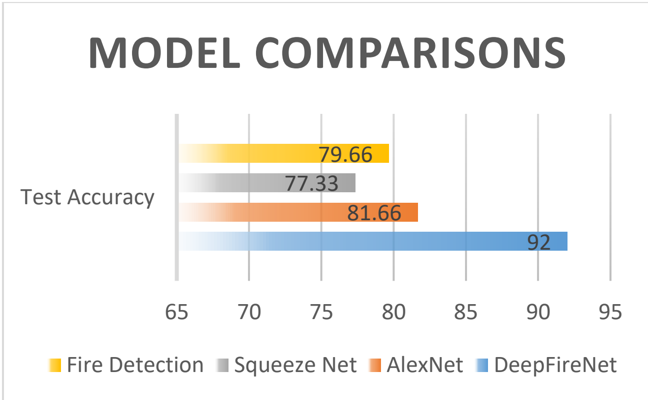

Figure 7: DeepFireNet Robustness

Figure 7 result shows that DeepFireNet performs well than other well-known models in terms of test accuracy and due to the minimum number of layers our model is not complex as other models.

VI. CONCLUSION

In this paper, we have introduced the DeepFireNet model for fire detection and compared it to existing convolutional neural network models. The comparison of fire detection was performed on the same images' dataset. The aim was to design a lightweight fire detection CNN-based model with the highest accuracy. We showed that even with a small number of images our proposed model is quite effective for the detection and classification of fire images. Our modal size is (376.4 kb) which is half of the baseline modal (683.1 kB) proposed by J. Gotthans et al. [13].

The measured accuracy of our proposed model DeepFireNet was 92.33% and in the base study, the presented accuracy of AlexNet was 81.66%, Fire Detection and Squeeze Net accuracy was 79.66% and 77.33% respectively.

In terms of execution time, our proposed model based on fewer network layers than other models due to its execution time of DeepFireNet was less than other CNN models.

In the future, we have planned to work on the video dataset for fire detection and also locating the location of the fire in video frames. The concept of transfer learning may be used to improve the modal performance but may also extend the size of the modal.

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