

FireNet: A Specialized LightWeight Fire & Smoke Detection Model For Real-Time IoT Applications

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A decorative light blue triangle is located in the bottom right corner of the slide.

Motivation

- Fires cause a huge losses and can occurs a numerous times.
- A precise, fast and portable solution is required.
- The current Deep Learning methods for computer vision have a poor trade-off between performance and model size.
- A lightweight neural network, trained from scratch, could be deployable in a Raspberry Pi.

Related Work

- Handcraft feature extraction
 - Motion
 - Color
 - Present problems with fire-like color objects
- Deep Learning Approach
 - Fine-tuned DLNN (AlexNet, GoogleNet, VGG16, ResNet)
 - Large on-disk size

Dataset

The **training dataset** is sampled from other datasets used in **previous works** and complemented with images obtained from **Google Images** and **Flickr**.

Its compile **1124 images with fire** and, **1301 with no fire**.

Testing dataset is composed of:

- 46 videos **with fire (19064 frames)**
 - 16 videos **(6747 frames)** and **160 images with no fire**
- and are sorted randomly



Fig. 1. Few images from our training dataset.

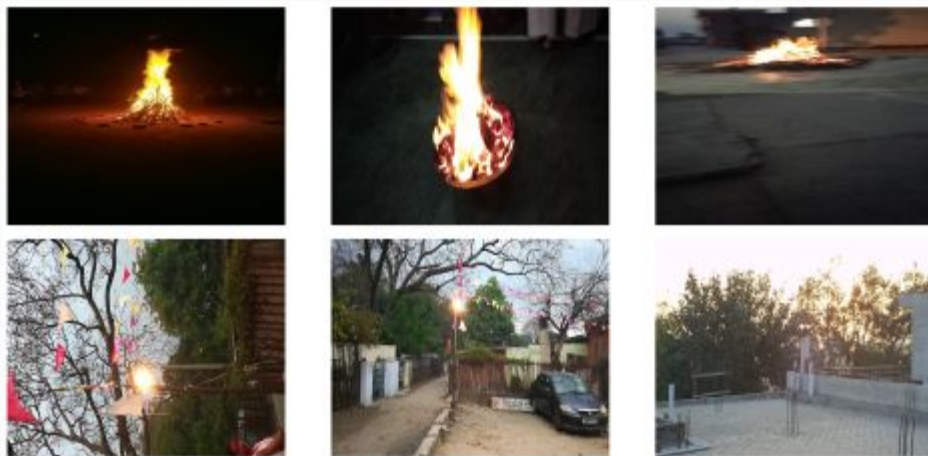


Fig. 2. Few images from our test dataset.

Proposed approach

System suitable as an **indoor fire detection unit**.

Lightweight Neural Network with
646818 params and on-disk size ~
7.45MB

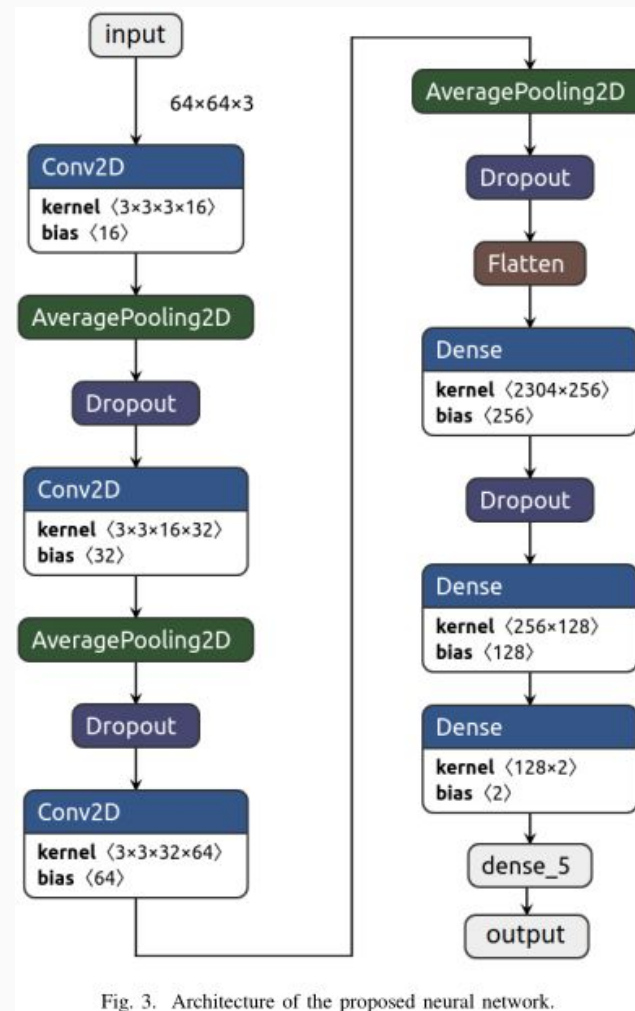


Fig. 3. Architecture of the proposed neural network.

Proposed approach

Raspberry Pi 3B unit for fire and smoke detection

Twilio for SMS/MMS Fire detection notification

Amazon Web Service's Simple Storage Service (**AWS S3**) for images or clip storage when the alarm is triggered

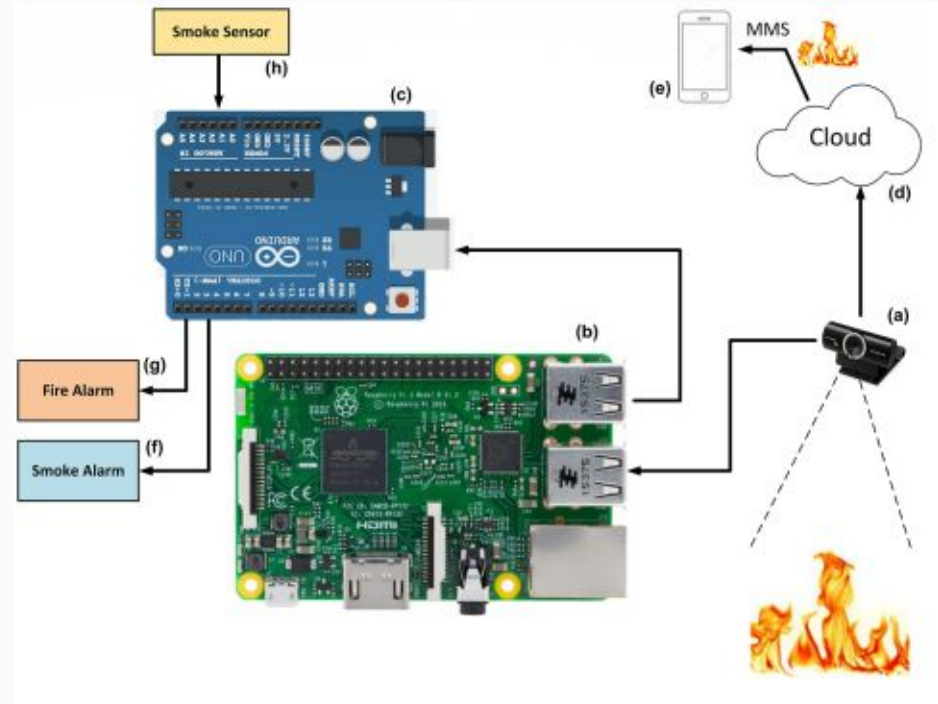


Fig. 4. Overview of the complete unit: (a) Camera (b) Raspberry Pi 3B (c) Microcontroller (d) Cloud storage and SMS/MMS service (Amazon S3 and Twilio) (e) End-user device for receiving fire alert (visual and textual) (f) Smoke alarm (g) Fire alarm with a different sound than smoke alarm (h) Smoke sensor for sensing smoke and thus, aiding in fire-smoke differentiation.

Results

From the dataset, **70% was used for training** and **30% for validation**.

The results obtained were performed against a **dataset used in previous work** and against the **compiled testing dataset**.

TABLE I
TEST PERFORMANCE OF 'FIRENET' ON OUR REAL-WORLD TEST DATASET

| Metrics | Our dataset (%) | Foggia's dataset (%) |
|-----------------|-----------------|----------------------|
| Accuracy | 93.91 | 96.53 |
| False Positives | 1.95 | 1.23 |
| False Negatives | 4.13 | 2.25 |
| Recall | 94 | 97.46 |
| Precision | 97 | 95.54 |
| F-measure | 95 | 96.49 |

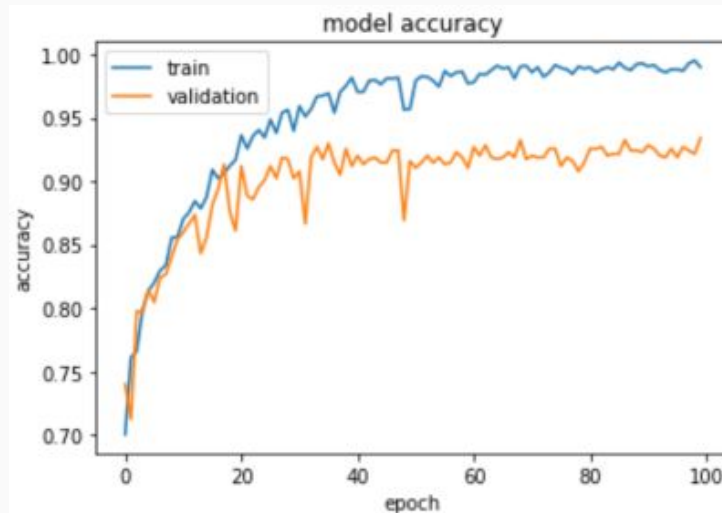


Fig. 5. Training and validation curves for model accuracy.

Problems found

- It doesn't present any **metrics for computational cost**.
- **Mislabeled images** on the training dataset result in **bad response** for the output classification.



```
FPS: 91  
NoFire: 0.18%  
Fire: 99.82%  
Fuego!
```


Proposed work

- Choose a better dataset for fire classification.
- Improve the Neural Network lightweight model.
- Add at least one computational cost measure.
- (optional) Extent the work to fire detection with a bounding box.

Thanks for your attention

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