IoT-based Fire and Smoke Detection in Smart Cities using Deep Learning

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Agenda

- Motivation
- What is a Smart City? Why Now?
- IEEE Standards enabling Smart Cities
- Overview of IoT-based Fire & Smoke Detection in Smart Cities
- Framework of Smart City IoT Architecture
- CNN Model for Fire & Smoke Detection
- Effectiveness of the Proposed Model
- Recommendations Using Industry Best Practices
- Conclusion
- Demo

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BY MARTA OLIVER-CRAVIOTTO / NOVEMBER 28, 2017

Santa Clara and San Mateo urge residents to register in alert systems after recent fires in California

PALO ALTO – The recent fires that swept through California's wine country have raised concerns over the appropriate use of emergency alert systems –whether it was sufficient to send alerts that are locally targeted and that require a previous registration. In San Mateo and Santa Clara counties, residents are being urged to sign up for local alert services.

AlertSCC and SMCAlert are two of the alert services offered by Santa Clara and San Mateo, respectively, but officials can contact the population through multiple ways, such as local alerts systems or communication via social media.

What is a Smart City?

- What's Smart?
- Old: Smart = Can think ⇨ Can compute
- Now: Smart = Can analyze, Can find quickly, Can delegate, Can decide

⇨ Communicate = Networking

Grid vs. Smart Grid, Parking vs. Smart Parking, Car vs, Smart Car,
Home vs. Smart Home, Campus vs Smart Campus, Lighting vs Smart Lighting

Smart = Connected

- City vs. Smart City

Why Now?

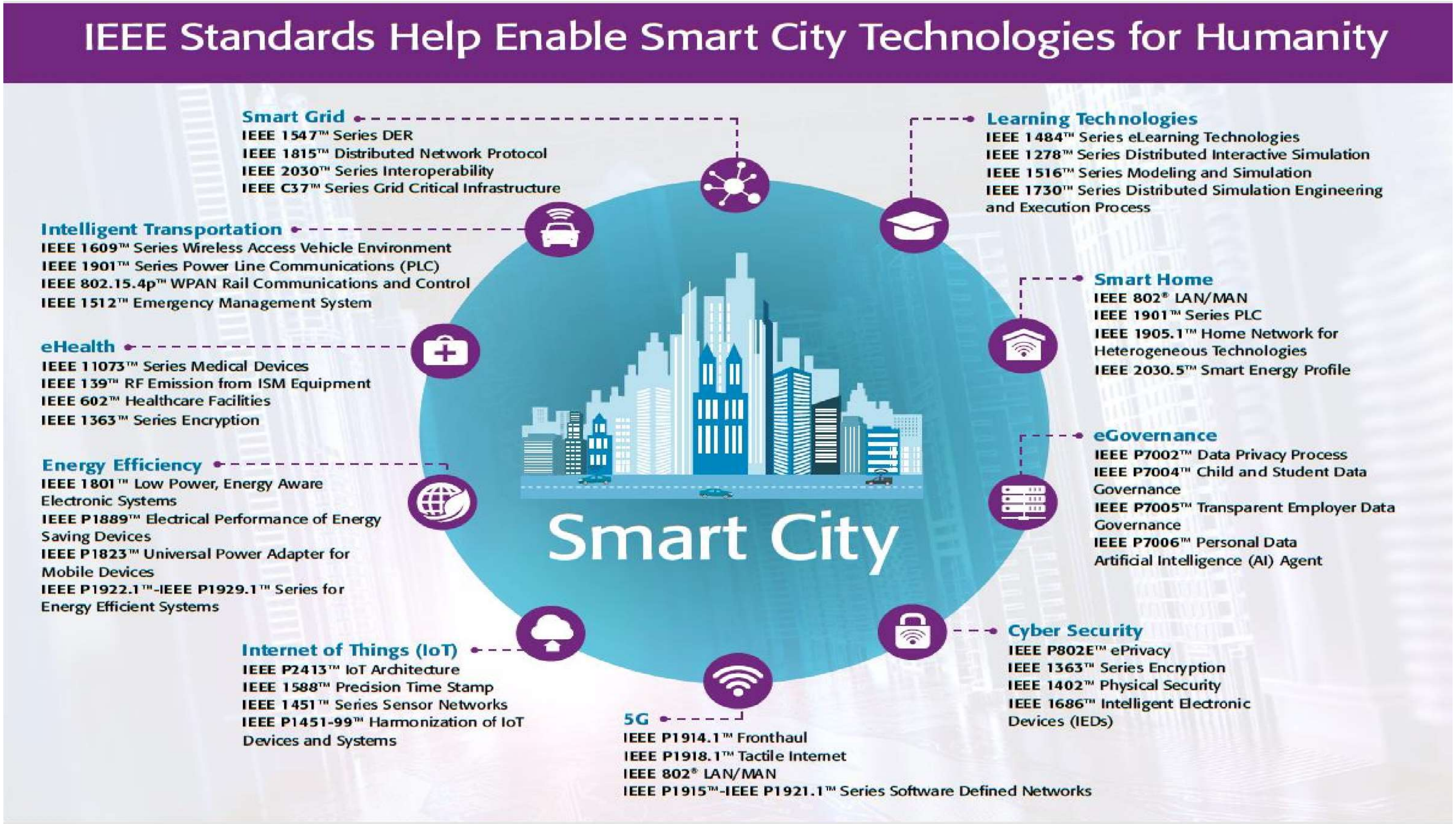
- Worldwide efforts for creating Smart Cities
- Big investment in Smart Technologies
- Sept 2015 - White House announced “Smart Cities” Initiative to help communities tackle local challenges and improve city services

ICT for Smart City

- **Acquisition** (IoT & Sensors): Provide real-time information about usage, availability, demand, state of resources
- **Interconnection** (Networking): FTTH, 4G LTE, IP multimedia system (IMS)
- **Integration**: Combine sensor data with other city data such as Geographical Information Systems (GIS), economic data, population data.
- **Analytics**: Predictive analytics, machine learning, data mining
- **Apps and Software**: Cloud Computing: Computation, storage, and ubiquitous accessibility, Service Oriented Architecture (SOA)

ICT (Information & Communication Technology) is the heart of Smart Cities

Source: Raj Jain: http://www.cse.wustl.edu/~jain/talks/smrtcit.htm



Source of the above image: IEEE an Open Platform for Smart Cities by Hermann Brand
https://www.itu.int/en/ITU-T/Workshops-and-Seminars/20180219/Documents/3.%20Hermann%20Brand.pdf

IEEE P2784: Technology & Framework for Smart City

- Smart Cities and related solutions need technology standards along with a cohesive process planning framework to ensure interoperable, agile, and scalable solutions that can be implemented and maintained in a sustainable manner.
- This framework provides a methodology for municipalities and technology integrators to use as a guide to plan for innovative and technology solutions for smart cities.
- This work is under development.

Public Safety for Smart Cities

- Alert and warning of the public is of vital importance in terms of emergency management and preparedness for large cities such as San José.
- One of the goals is to deploy integrated mass warning systems that can provide emergency alert and messaging to 90% of the population within 10 minutes of notification initiation.
- Prediction and early detection of fire and smoke in smart cities can reduce large-scale damage and improve public safety significantly.

Emergency Services: Fire and Smoke Detection

- Several tools and technologies have been used to detect fire or smoke.
- Most of the traditional methods use sensor-based tools.
- The main disadvantage of such sensors is that they can generally only recognize fire or smoke in the vicinity where they are installed.
- This limits their effectiveness in large covered areas.
- Fire or smoke detection sensors are unable to provide adequate information about the direction, location, or magnitude of the fire.

Fire and Smoke Detection

- We are investigating a CNN-based deep learning model for fire and smoke image detection.
- This method is capable of classifying both smoke and fire images at the same time.
- It offers many advantages and rudimentary results are promising.

Overview of IoT-based Fire and Smoke Detection in Smart Cities

Smart City Fire and Smoke Problem

- Smoke and fire detection in IoT environment is a primary component of early disaster-related event detection in smart cities.
- Early detection of smoke and fire in all weathers (foggy, rainy, windy, snowy) and any time of day and night is a key event detection requirement to mobilize resources and help residents to reduce human and property damages.

Smart City Fire and Smoke Problem

Potential causes for fire and smoke

a. Electrical equipment including transformers, air conditioners and pumps can catch fire when overloaded in continuous operating conditions or, in high heat environment or, in very low temperature cold environment
b. Electrical short circuit in homes, businesses caused or, by power line fall on trees due to storm and rain
c. Bush fires, Campfires & Picnic
d. Earthquake
e. House, Factory, vehicle fire and smoke

Fire & Smoke Detection: Requirements & Challenges

1. Early incident detection and identification
   a. High value to detect and suppress smoke and fire prior to reaching an uncontrolled state. According to experts, a typical brush fire tends to double in size every few minutes while in high-wind conditions or extremely dry conditions, the rate of growth can be much greater.
2. Intelligence at every level of IoT to avoid data explosion
   a. Intelligence and analytics processing of data is required at every level of IoT
3. Challenges of smoke detection
   Automatic smoke detection using computer vision techniques is still an open challenge due to various reasons such as the similarity with other natural objects like fog, clouds and shadows, inconsistency of smoke density and motion and complex visual pattern of smoke

Fire & Smoke Detection: Requirements & Challenges

3. Deployment of sensors, equipment based on city regulation
4. Optimize resource utilization and conserve power
    a. Minimize the utilization of sensing, communication & data processing resources to reduce energy consumption in favor of increased battery life with regulations
    b. out endangering the early and accurate detection of fire and smoke

Framework of Smart City IoT Architecture

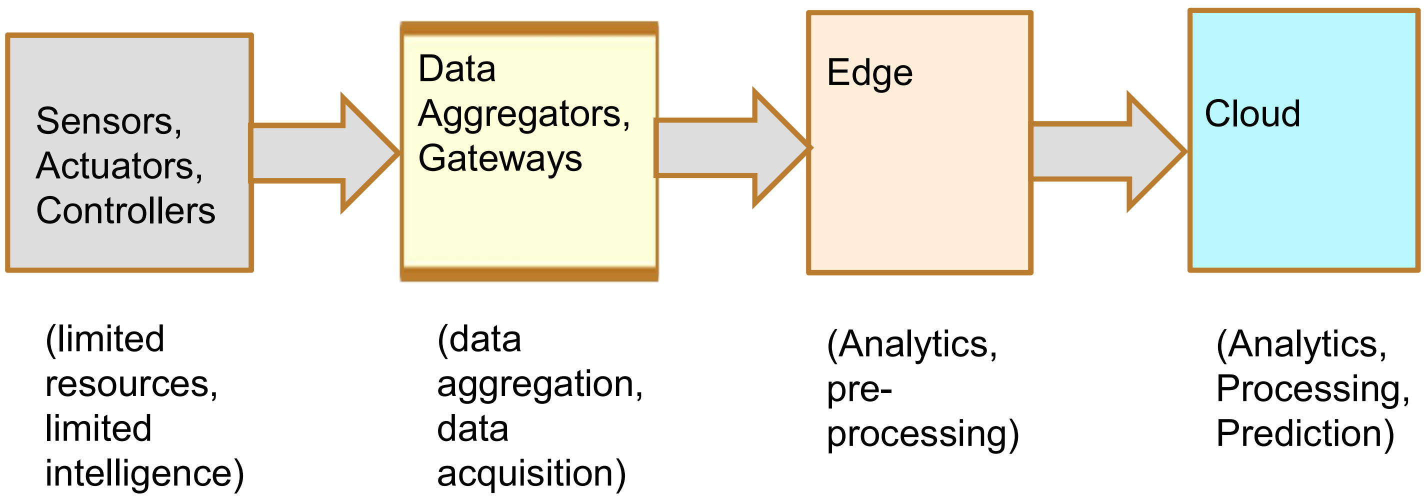
Smart City IoT Stages

Smart city IoT can be divided primarily into following four stages:

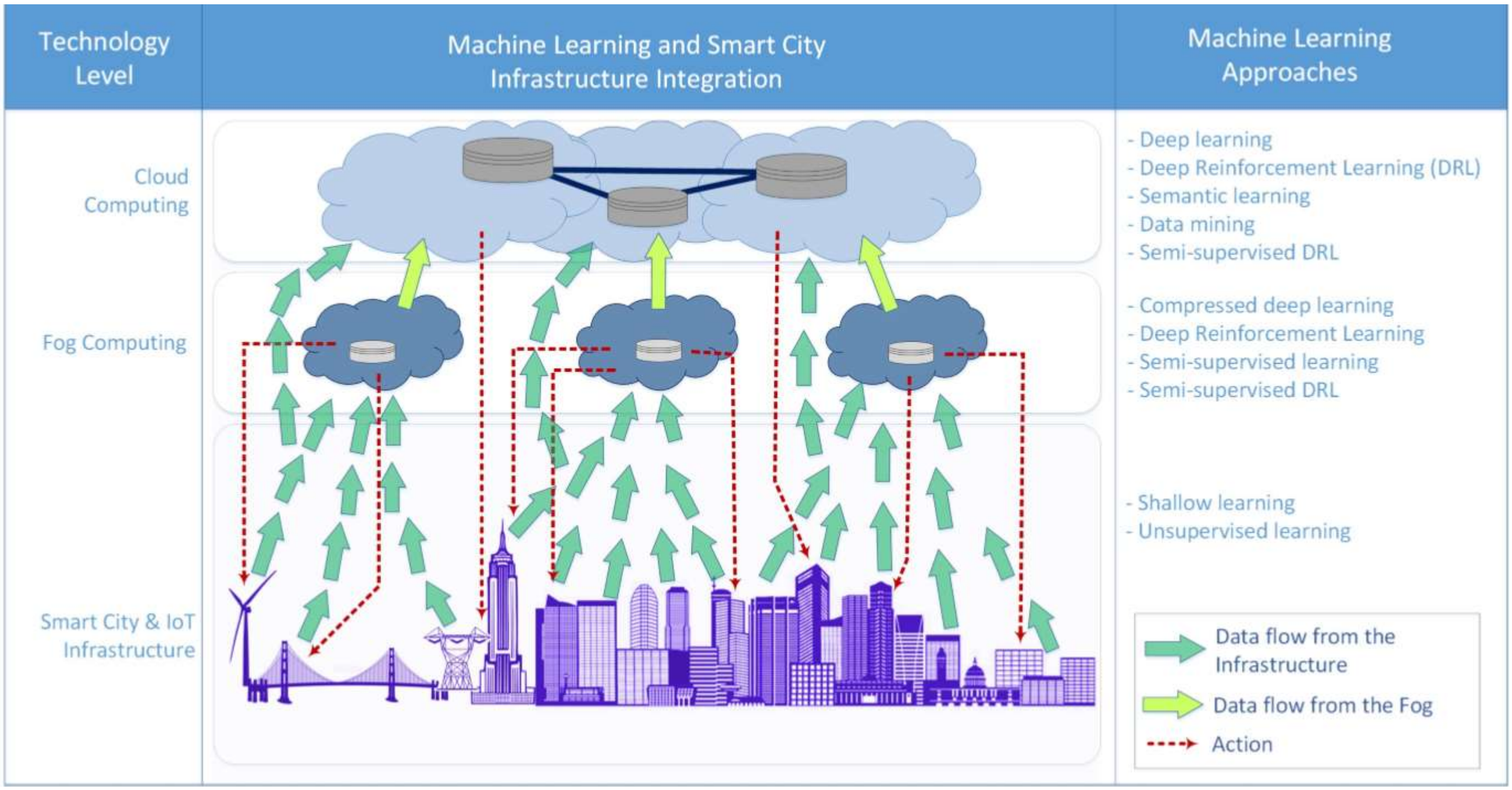
- Sensors, Actuators, Controllers, smart dust (limited resources, limited intelligence), smart dust with GPS, Drone/UAV
- Data Aggregators, Gateways (data aggregation, data acquisition)
- Edge (analytics, preprocessing)
- Cloud (analytics, prediction, processing, management)

IoT Stages

IoT can be divided primarily into following four stages as shown in the following diagram:



Levels of Intelligence in Smart City



Source of the above image: Enabling Cognitive Smart Cities Using Big Data and Machine Learning: Approaches and Challenges by Mehdi Mohammadi

Sensors, Actuators & Controllers

Sensors, Actuators & Controllers

- Sensors
  - Smart dust combines smoke sensing (ionization and photo electric), computing, sensing of humidity, temperature, CO, CO_2 & wind speed, wireless communication capabilities and autonomous power supply within small envelope at low cost in large volume of deployment. Large number of smart dust sensors will be deployed and will be connected in mesh configuration and will communicate when smoke is detected. Some of the smart dust sensors can be more intelligent node with GPS and will be able to provide time stamp, exact location and direction of smoke and wind travel by combination of data from the intelligent nodes.
    - Ionization smoke sensors – are generally mode responsive to flaming fires
    - Photo electric smoke sensors – are generally mode responsive to smoldering fires
  - Vision sensors for smoke and fire detection
  - UAV and/or drone to augment and speed up detection of smoke and fire from Aerial

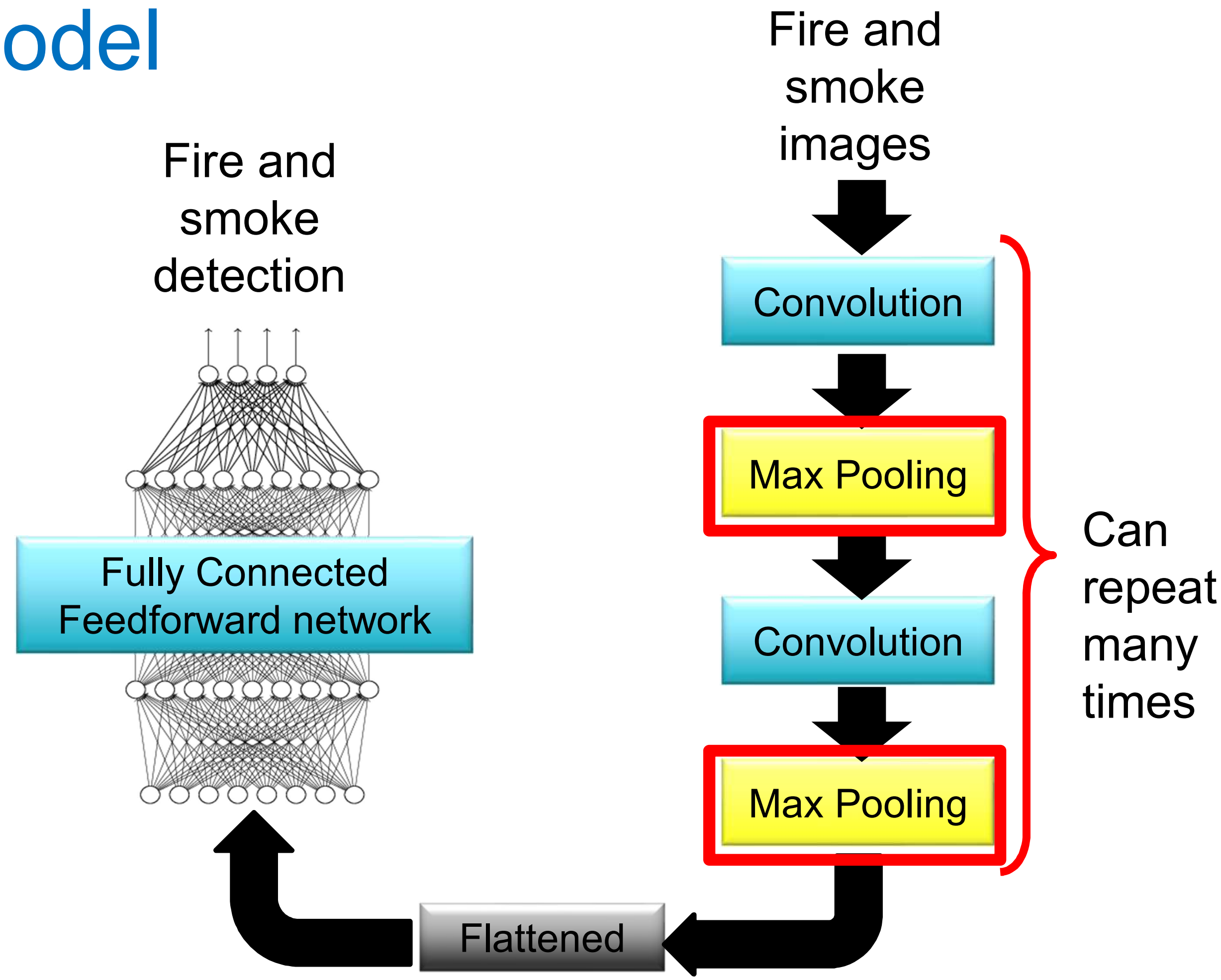
Data Aggregator, Gateway, Concentrators: Data Aggregation, Measurement, Data Acquisition

Data Aggregator

- Data Aggregator does the combined classification from various sensing sources
  - Does data aggregation
  - Selects and classifies data by filtering data, detecting outliers and rejecting them
  - Low latency for aggregating data
  - Energy efficient

CNN Model Using Deep Learning for Fire & Smoke Detection

CNN Model


Fire and smoke images
Convolution
Max Pooling
Convolution
Max Pooling
Can repeat many times
Flattened
Fully Connected Feedforward network
Fire and smoke detection

Edge: Analytics & Preprocessing

Edge: Analytics & Preprocessing – Model for Edge

Functionality for Edge application

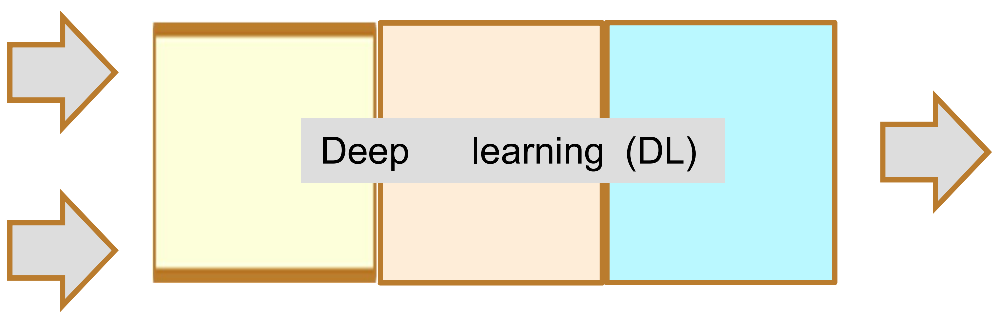
- Analytics at the Edge
- Edge based computing and does preprocessing for cloud
- Realtime response and lower latency
- Better localized accuracy for IoT
- Increased performance
- Uses TFlite
- Useful for application like smoke, fire detection that needs real time response

Edge: Analytics & Preprocessing

- Deep learning way of finding Analytics at the edge
  - Edge servers are smaller in size with limited storage and kept at various locations
  - Selection of appropriate model allows low latency, real time operation and high QoS

Classification, critical data trend and analytics on Smoke and fire detection data

Environment test data such as Fog, Cloud



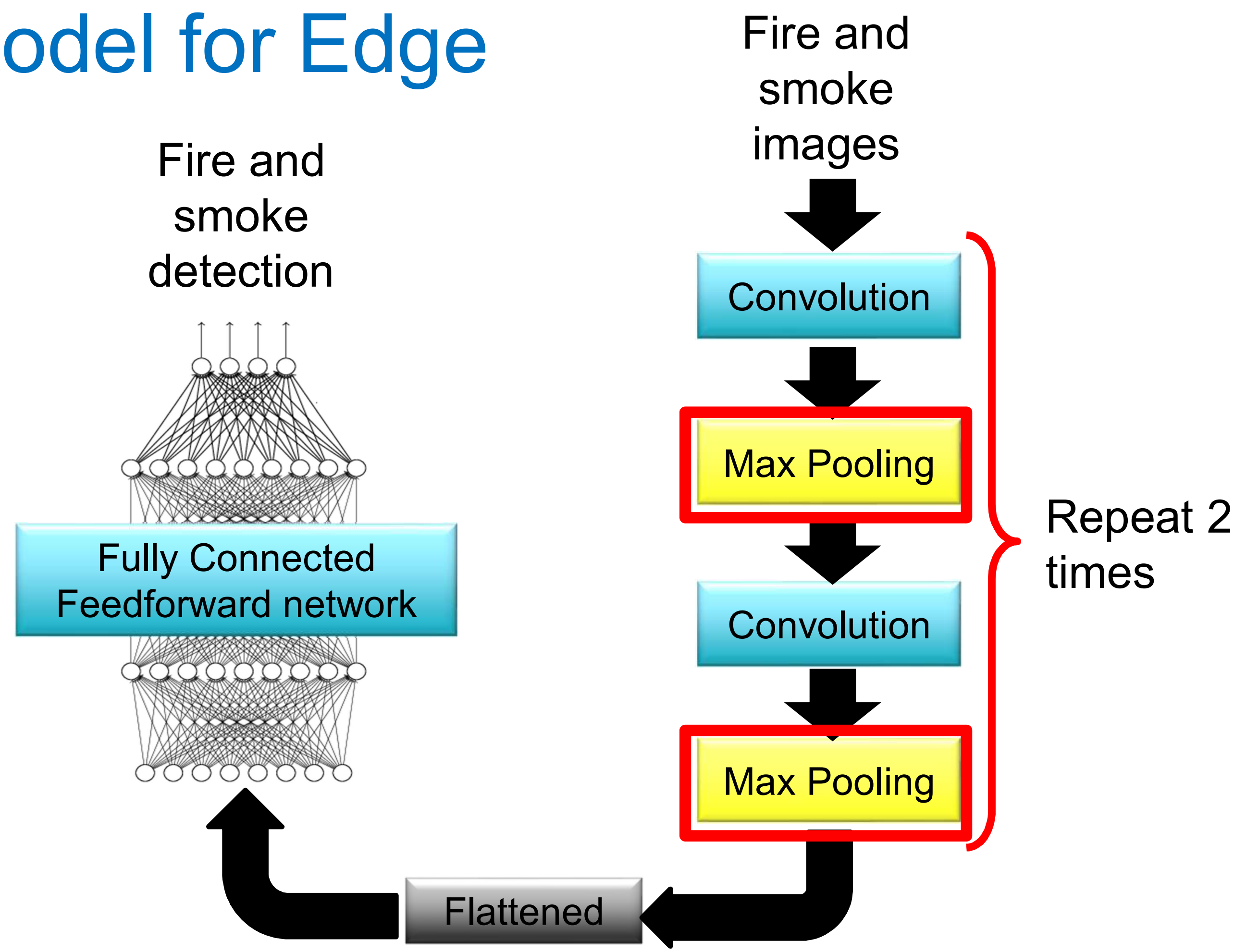
Smoke and fire detection in presence of fog, cloud in a short time

Trained combined detection with monitoring feature extraction (Coarse low level features)

Trained combined detection with monitoring feature extraction (Higher level features)

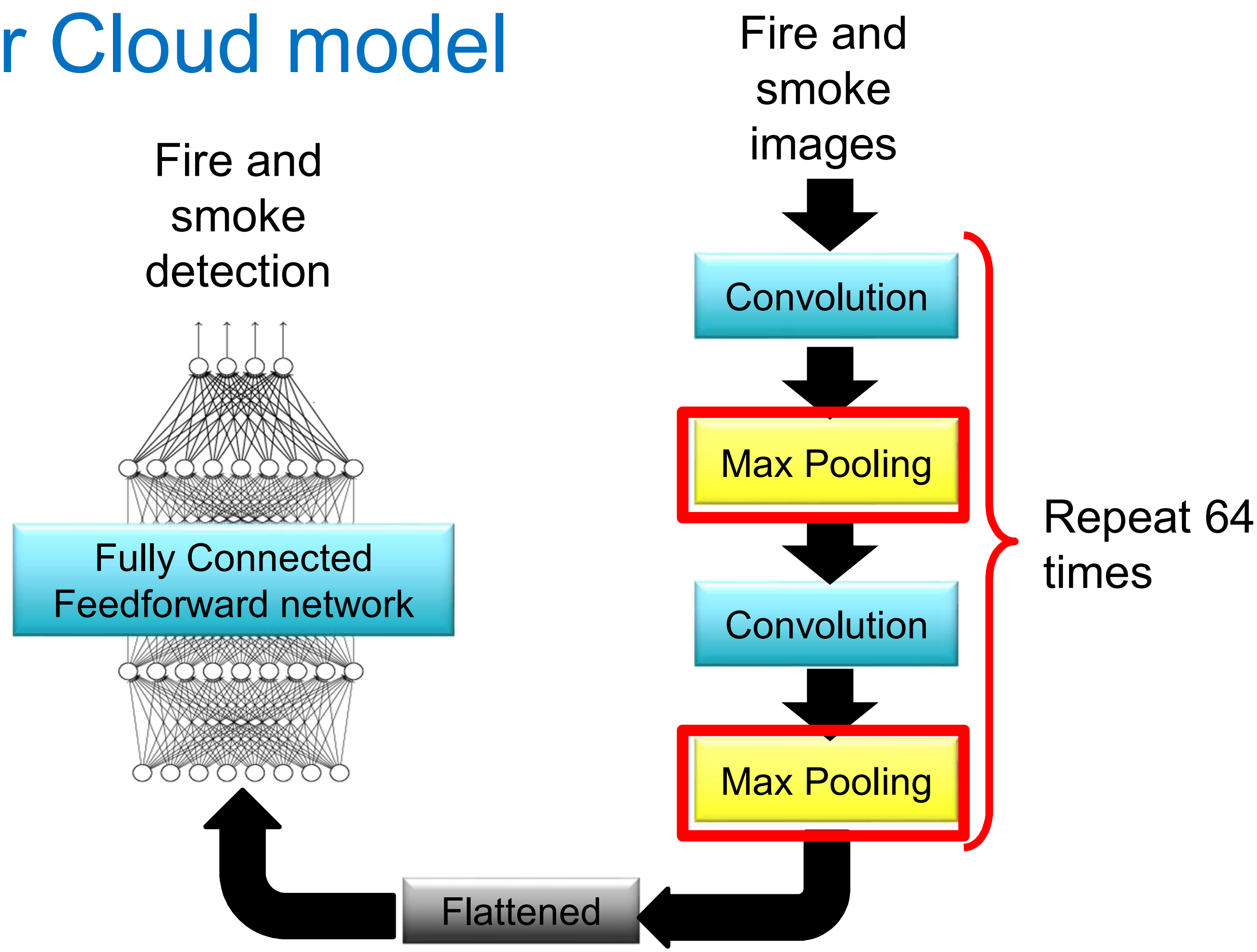
Trained Classifier combined detection with monitoring (Classification of fire and smoke)

CNN Model for Edge



Cloud: Analytics & Processing

CNN for Cloud model



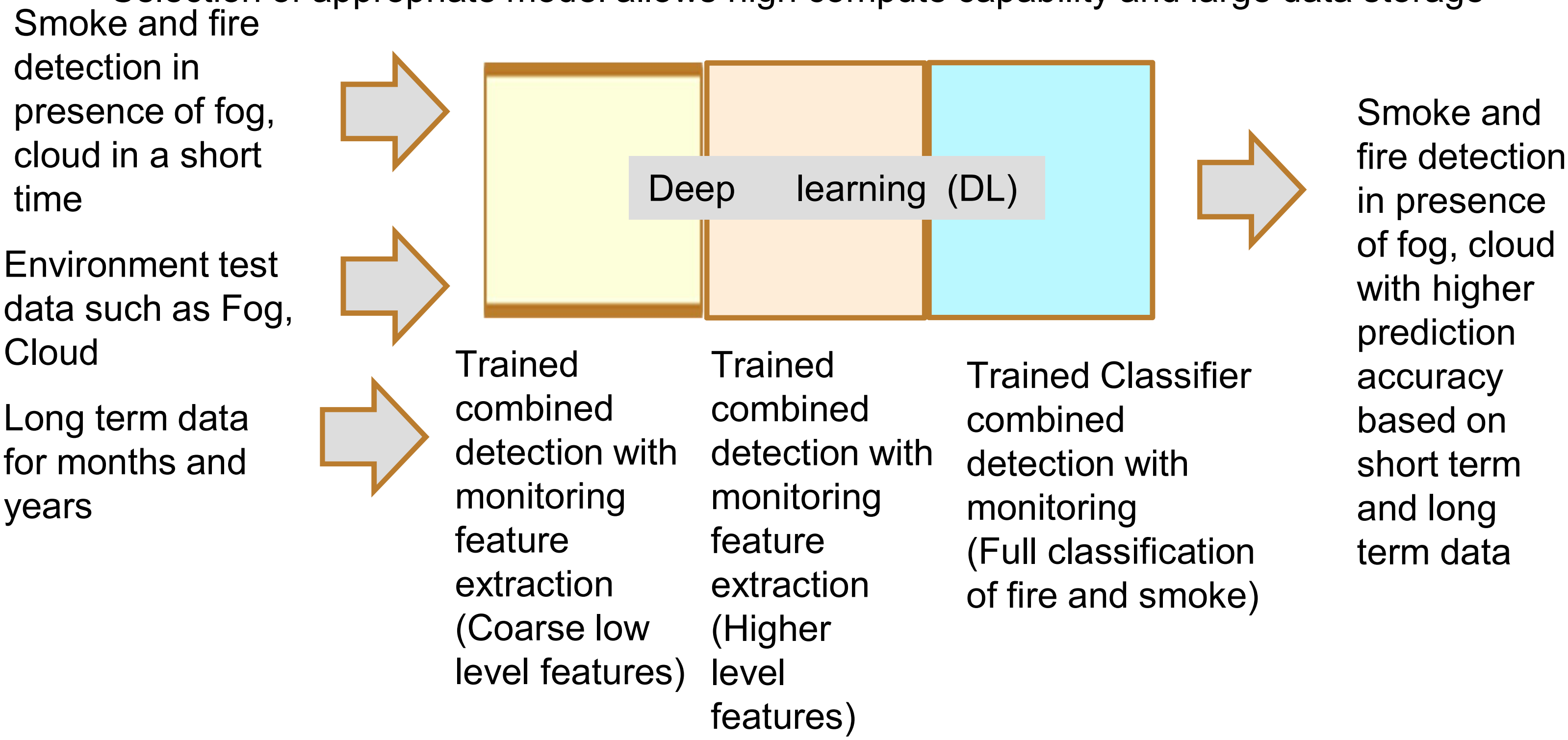
Cloud: Analytics & Processing

- Analytics & prediction
- Full processing of all the data and classification on a full model
- Combines short term data with long term data to provide thorough analytics and prediction
- Predicts smoke and fire by looking at long term and short term data
- Long term data may include similar data at same time in past history (months, years) that relates to similar temperature, humidity, wind speed fog etc.
- Short term data will include all data from all the sensors on the ground and on aerial
- Uses full TF for analysis, Higher accuracy of prediction
- Relatively long latency compared to Edge

Cloud: Analytics & Prediction

Deep learning way of Prediction from cloud with higher accuracy

- Cloud servers is very large in size and is centralized
- Selection of appropriate model allows high compute capability and large data storage



Proposed Model Effectiveness

- CNN limitations
  - CNNs lays in the amount of data you provide to them. CNNs perform poorly with less data. CNNs could have very large number (millions in some cases) of parameters. With small dataset, would run into an over-fitting problem.
  - CNNs is more strong and provides better performance with large set of data.
  - Currently we have very limited datasets. Once we get enough datasets, we will be able to accurately evaluate our model.

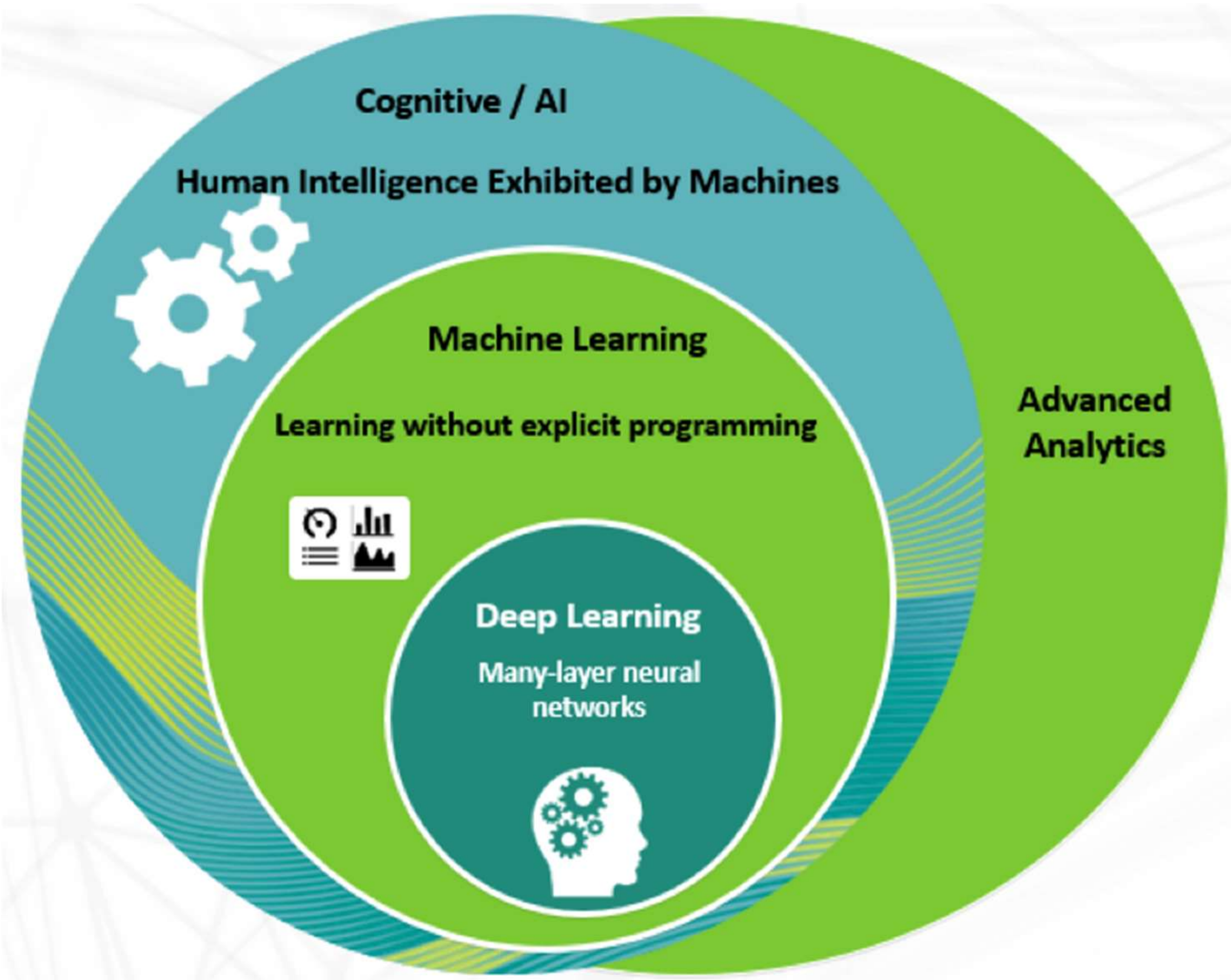
Industry Best Practices

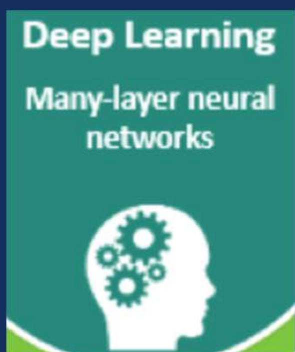
- CNNs have the ability to learn location invariant features automatically by leveraging a network architecture that learns image features for fire and smoke in smart city environment, as opposed to having them hand-engineered (as in traditional engineering).
- Computer vision and deep learning present challenges when going into production. These challenges include:
  - Getting enough data of good quality and managing expectations on model performance
  - The result depends on how good and how large the data set is and is still not there to replace human. Need to be pragmatic and be careful when deploying CNN.

Conclusion

- Timely fire and smoke detection in Smart Cities is a challenging problem.
- Smoke and fire detection overview in a Smart City is discussed.
- IoT architecture and various stages are presented.
  - Sensor and aggregation stages functions are discussed.
- CNN model for fire and smoke detection is proposed.
- Currently we have very limited datasets. Once we get enough datasets, we will be able to accurately evaluate our model.
- Recommendations using industry best practices are discussed.
- In our future work, we will delve into other approaches for further improvement.

Demo

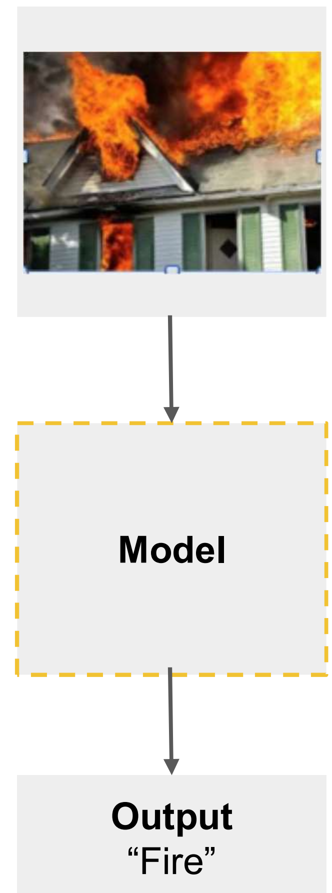

Cognitive / AI
Human Intelligence Exhibited by Machines
Machine Learning
Learning without explicit programming
Deep Learning
Many-layer neural
networks
Advanced
Analytics



What is DL?

What’s a machine learning?

Use **algorithms** to **learn** from data (a.k.a **Training**)
Algorithms are known as **models**
Models perform **prediction** (a.k.a **inference**)



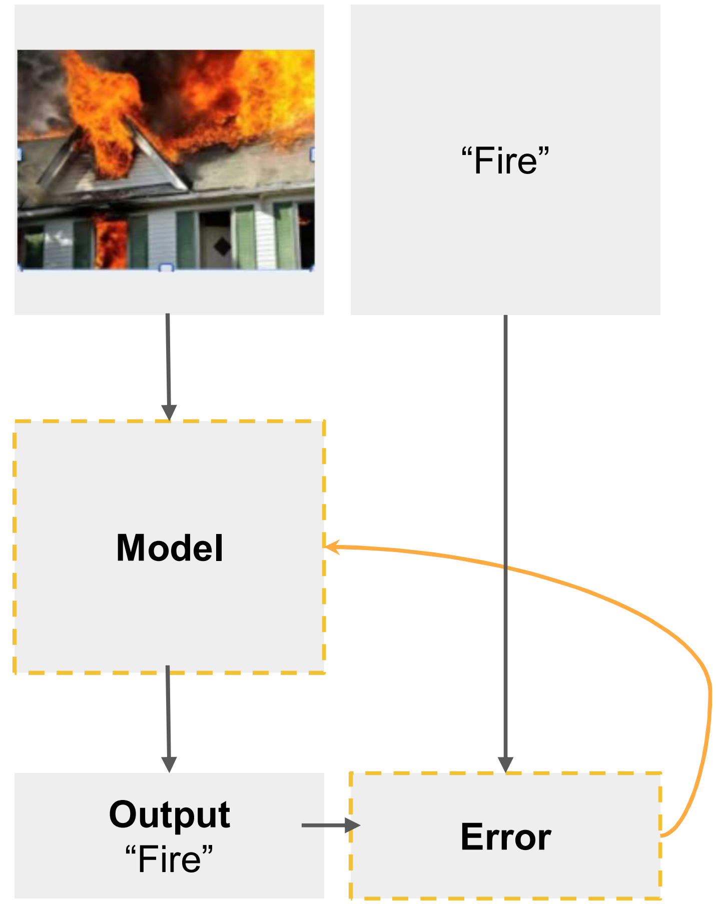
What's a machine learning?

Use **labeled data** to improve models

labeled data = Input data + predictions

Errors used to **improve** the model

We need a Framework to make machine learning predictions easier

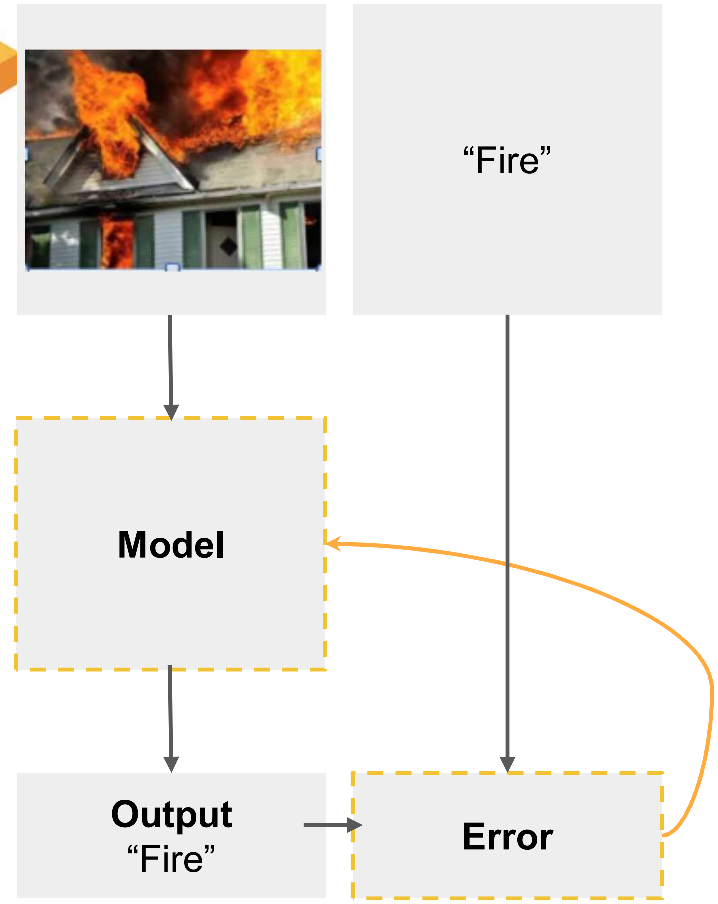


TensorFlow

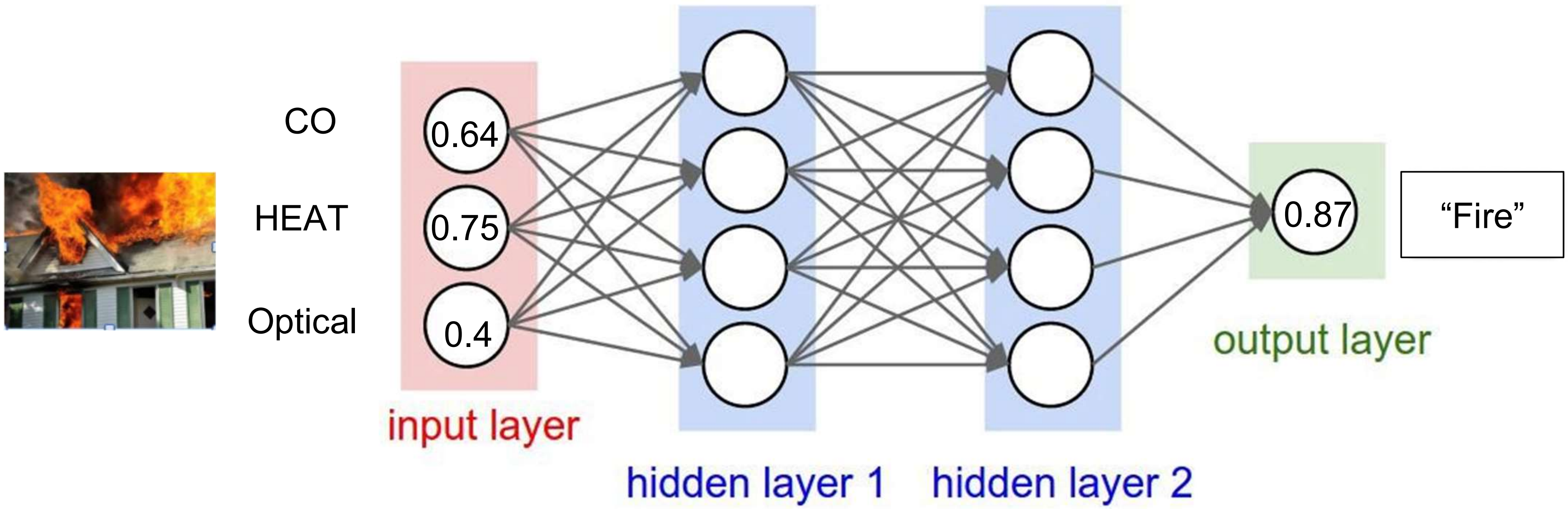
TensorFlow is google's framework for machine learning.

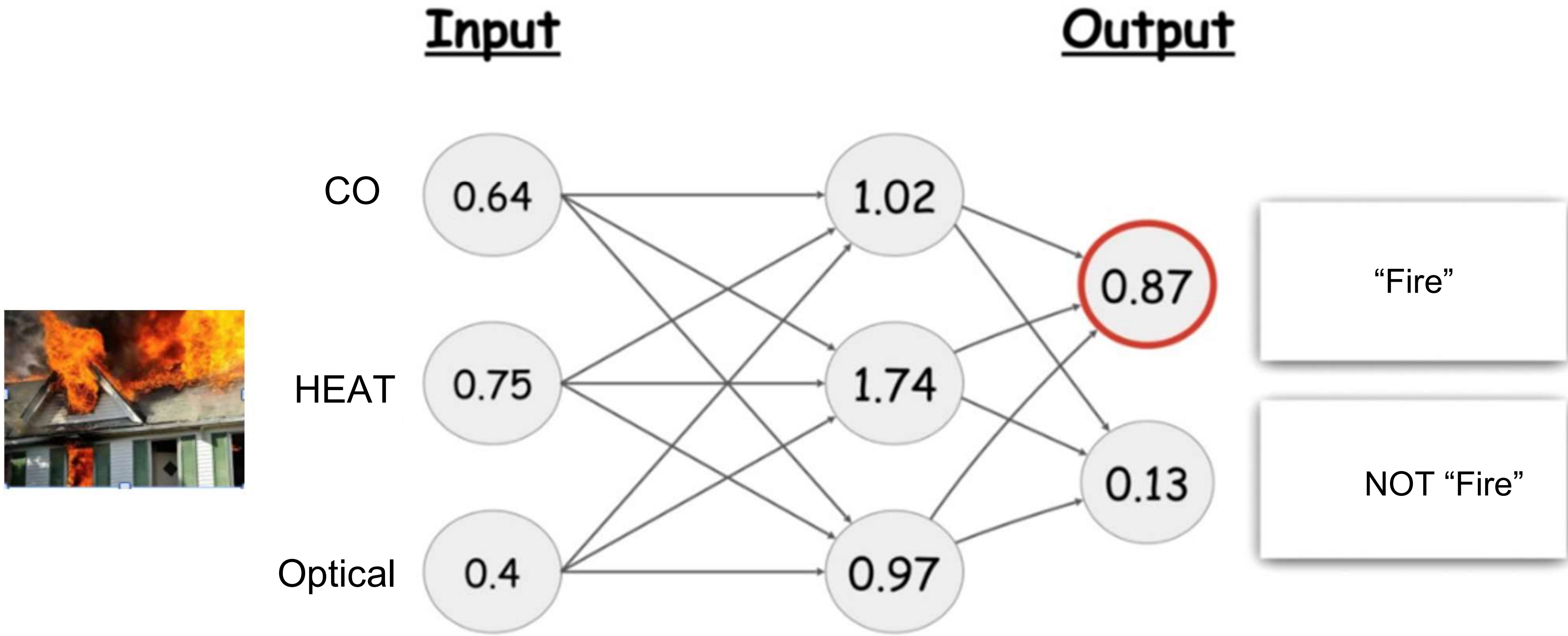
It makes it easy to build and train **neural networks.**

It is cross platform, works with CPUs, GPUs, TPUs, as well as Mobile devices, and Embedded Platforms.

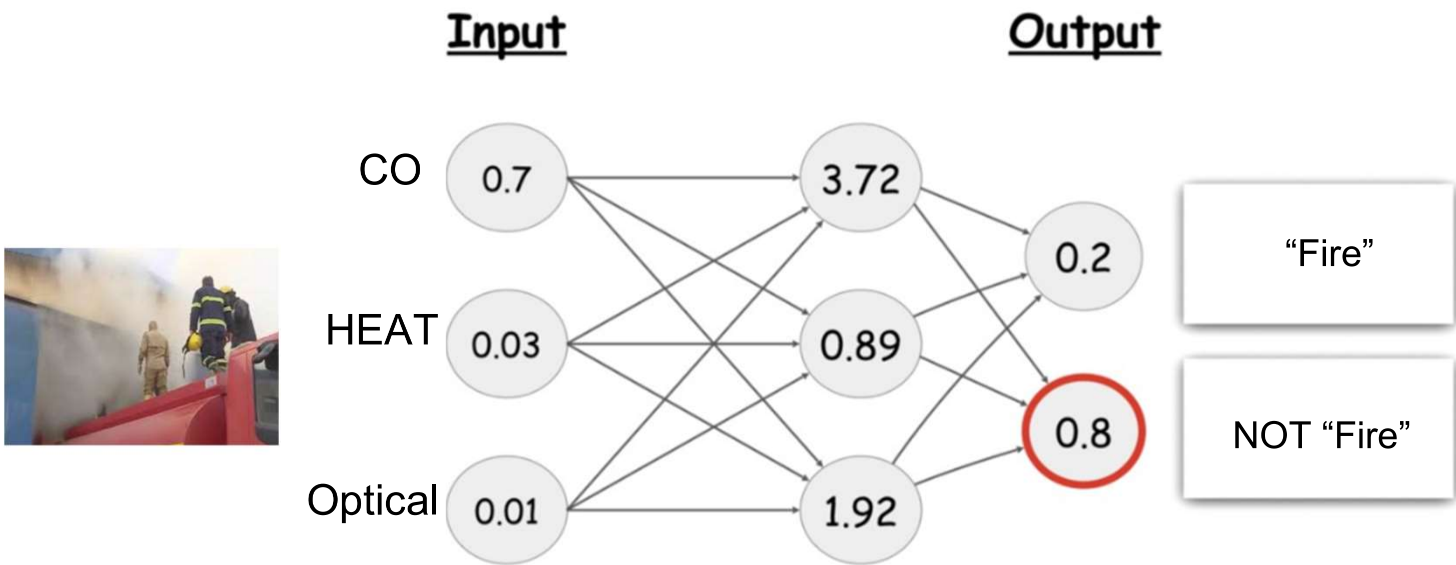


TensorFlow builts and Train Neural Networks





Input
Output
CO
HEAT
Optical
0.64
0.75
0.4
1.02
1.74
0.97
0.87
0.13
“Fire”
NOT “Fire”


Input
Output
CO
HEAT
Optical
0.7
0.03
0.01
3.72
0.89
1.92
0.2
0.8
"Fire"
NOT "Fire"

Optimization

Make your models even smaller and faster.

Optimization

Quantization

New tools

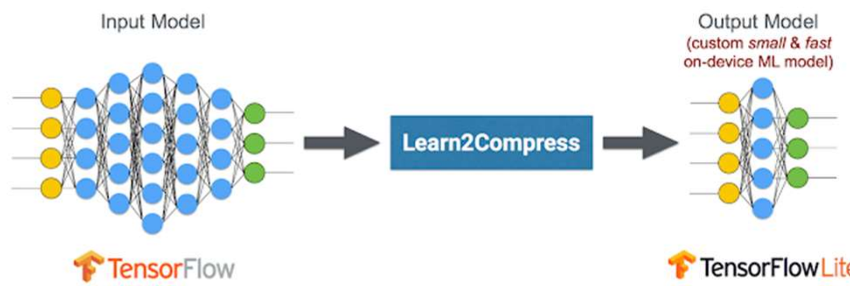
- Post-training quantization with float & fixed point
- Great for CPU deployments!

Optimization

Quantization (post-training)

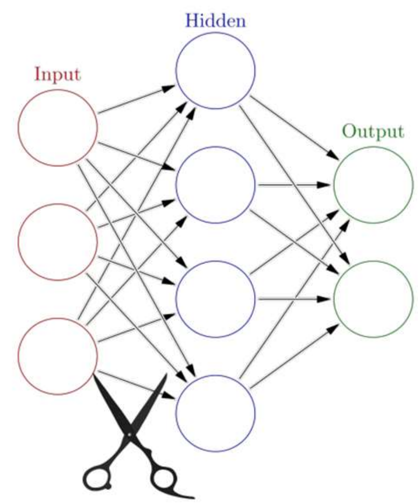
Optimization

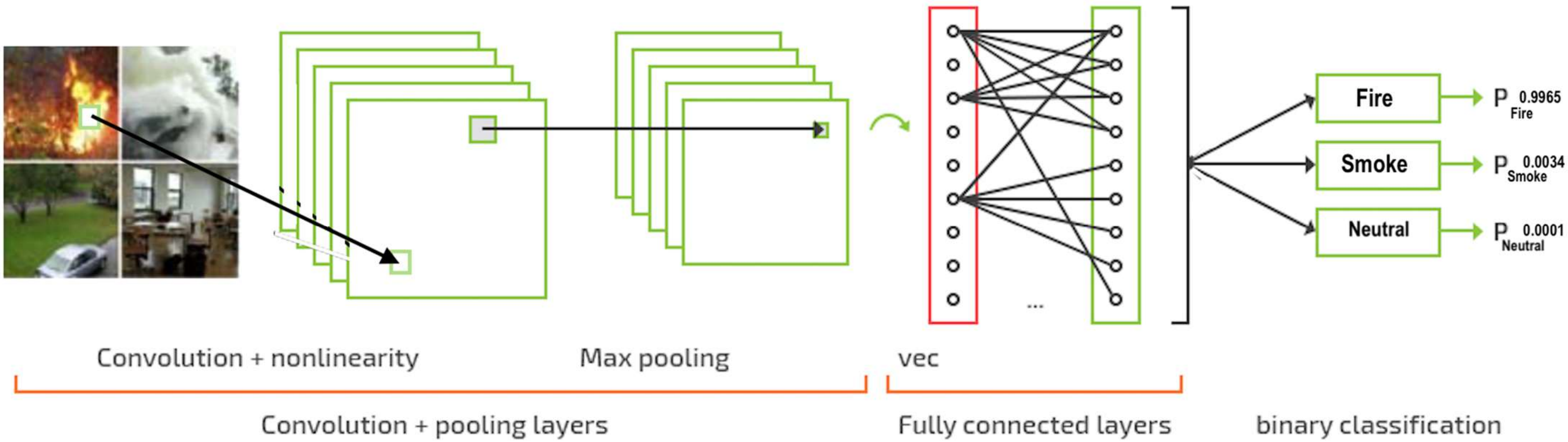
Connection pruning



Benefits

- **Smaller models.** Sparse tensors can be compressed.
- **Faster models.** Less operations to execute.





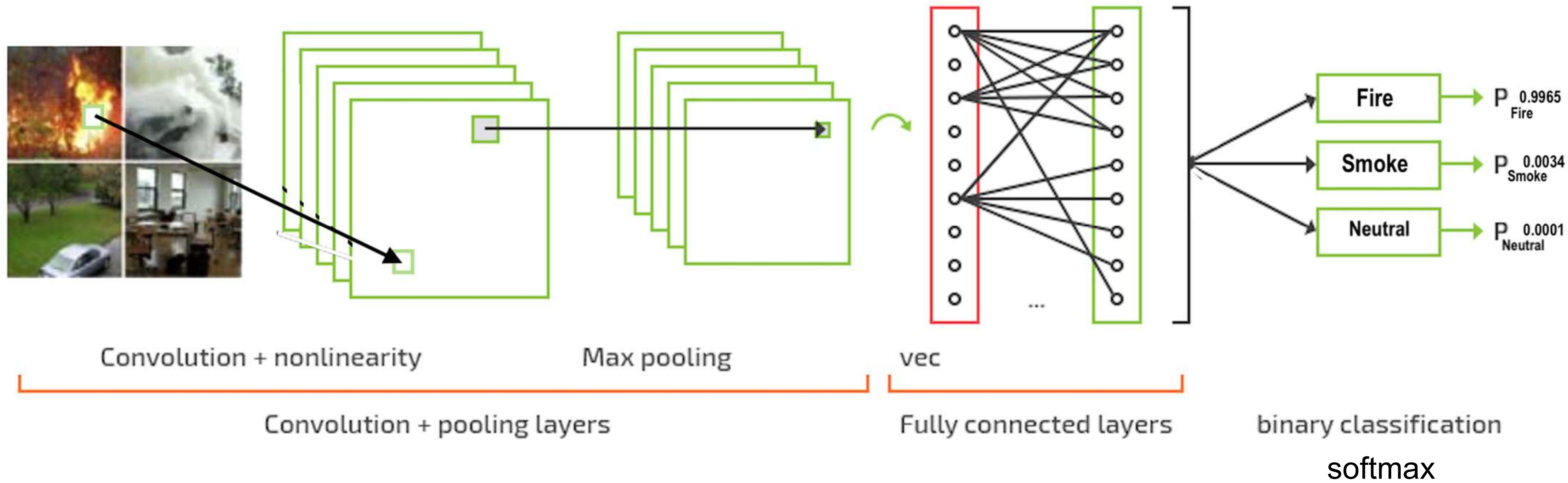
softmax

Convolution layers → apply specific filters to the image

Pooling layers → downsample the image data

Max Pooling → keeps feature map to get its maximum & discard others

FC layers → perform classification to features, every node in the layer is connected to every node in the preceding layer



Binary classification → given a problem with 3 possible solutions, 3 binary classifiers, outcome is only ONE.

Softmax assigns decimal probabilities to each class in a multi-class problem.
Those decimal probabilities must add up to 1.0. → $P_{Fire} + P_{Smoke} + P_{Neutral} = 1.0$

Fire – Flame - Dataset

An image dataset for training fire and frame detection AI

Indented block Fire-Flame-Dataset is a dataset collected in order to train machine learning model to recognize Fire, smoke, and neutral(images without fire or smoke).
This a dataset containing about 3000 images and 3 classes which include:

- Fire
- Smoke
- Neutral

There are 1000 images in each category and 900 for train and 100 for testing

Training and Prediction

The model was trained with train with resnet50 and a accuracy of 85% on the test data was achieved.

Some of the prediction results

'Image of:', 'Class: Fire', 'Confidence score: 1.0'

('Image of:', 'Class: Smoke', 'Confidence score: 0.9970703125')

('Image of:', 'Class: Neutral', 'Confidence score: 0.99365234375')

('Image of:', 'Class: Fire', 'Confidence score: 0.990234375')

('Image of:', 'Class: Smoke', 'Confidence score: 0.4462890625')

Demo:

Link