IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

FIRE AND SMOKE RECOGNITION USING DEEP LEARNING

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Abstract

Detecting fire and smoke from visual scenes is a demanding task, due to the high variance of the color and the texture. A number of smoke and fire image classification approaches have been proposed to overcome this problem. However, most of them rely on either rule-based methods or on handicraft features. To achieve high accuracy fire and smoke image detection, an algorithm named Convolutional Neural Network (CNN) is used. Instead of using traditional rectified linear units or tangent functions, adaptive piecewise linear units in the hidden layers (convolution + RELU, pooling) are used. Convolutional Neural Network are shown to perform very well in area of object classification. This network has the ability to perform feature extraction and classification within the same architecture. A dataset of fire and smoke images is created to train and evaluate this model. To solve the problem caused by training the network on a limited dataset, the number of available training images should be improved using traditional data augmentation techniques

Key words: Data Augmentation, CNN Algorithm, Convolution+RELU, Pooling.

Introduction

In the economic development, the fire control has become great challenge in the constructions because of the increasing scale and complexity. Therefore, we need fire detection and alarm with high sensitivity and accuracy to reduce fire losses. Traditional fire detection technologies, like smoke and heat detectors, are not suitable for large spaces, complex buildings, or spaces with many disturbances. Due to the limitations of above detection technologies, missed detections, false alarms, detection delays and other problems often occur, making it even more difficult to achieve early fire warnings.

Recently, image fire detection has become a trend in the research part. This technique has many advantages like early fire detection, high accuracy, flexible system installation, and the capability to effectively detect fires in large spaces and complex building structures. It processing image data from a camera by algorithms to determine the presence of a fire in images. Therefore, the detection algorithm is the main part of this technology, it directly determining the performance of the image fire detector.

There are three main stages in the process of image fire detection algorithms, including image preprocessing, feature extraction, and fire detection. Among, feature extraction is the core part in algorithms. Traditional algorithm depends on the manual selection of fire feature and machine learning classification. Image recognition algorithms based on convolutional neural networks (CNNs) can automatically learn and extract complex image features effectively. This kind of algorithms has attracted great concerns and achieved excellent performance on visual search, automatic driving, medical diagnosis, etc.

Literature survey

Data augmentation is a strategy that enables practitioners to significantly increase the diversity of data available for training models, without actually collecting new **data**. **Data** augmentation techniques such as cropping, padding, and horizontal flipping are commonly used to train large neural networks

- Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning.
- Artificial neural networks (ANNs) were inspired by information processing and distributed communication nodes in biological systems. ANNs have various differences from biological brains. Specifically, neural networks tend to be static and symbolic, while the biological brain of most living organisms is dynamic (plastic) and analogue
- The adjective "deep" in deep learning refers to the use of multiple layers in the network.

Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions

- A Convolutional Neural Network (ConvNet /CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

A ConvNet is able to successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better

1.Convolutional Layer

This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (MxM).

The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image.

2. Pooling Layer

In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations.

In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer

3. Fully Connected Layer

The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last few layers of a CNN Architecture.

In this, the input image from the previous layers are flattened and fed to the FC layer. The flattened vector then undergoes few more FC layers where the mathematical functions operations usually take place. In this stage, the classification process begins to take place.

4. Activation Functions

Finally, one of the most important parameters of the CNN model is the activation function. They are used to learn and approximate any kind of continuous and complex relationship between variables of the network. In simple words, it decides which information of the model should fire in the forward direction and which ones should not at the end of the network.

It adds non-linearity to the network. There are several commonly used activation functions such as the ReLU, Softmax, tanH and the Sigmoid functions. Each of these functions have a specific usage. For a binary classification CNN model, sigmoid and softmax functions are preferred an for a multi-class classification, generally softmax us used.

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```
#LeNet-5 CNN Architecture
model = keras.Sequential()
model.add(layers.Conv2D(filters=6, kernel_size=(5, 5), activation='relu', input_shape=(32,32,1)))
model.add(layers.AveragePooling2D())
model.add(layers.Conv2D(filters=16, kernel_size=(5, 5), activation='relu'))
model.add(layers.AveragePooling2D())
model.add(layers.Flatten())
model.add(layers.Dense(units=120, activation='relu'))
model.add(layers.Dense(units=84, activation='relu'))
model.add(layers.Dense(units=10, activation = 'softmax'))
```

Figure 1 Model creation

System design

Systems design is the process of defining the architecture, product design, modules, interfaces, and data for a system to satisfy specified requirements. Systems design could be seen as the application of systems theory to product development.

Convolution Layer

Convolution is the first layer to extract features from an input image. Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel.

- An image matrix (volume) of dimension **(h x w x d)**
- A filter **(f_h x f_w x d)**
- Outputs a volume dimension **(h - f_h + 1) x (w - f_w + 1) x 1**

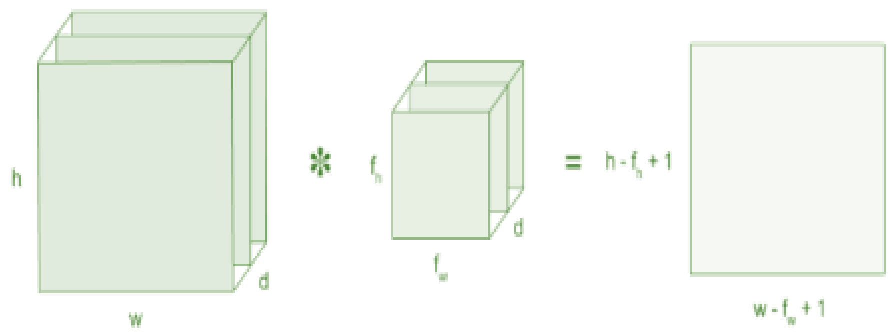

Figure 2 Convolution layer

ReLU

ReLU stands for Rectified Linear Unit for a non-linear operation. The output is ***f(x) = max (0, x).*** ReLU's purpose is to introduce non-linearity in our ConvNet. Since, the real-world data would want our ConvNet to learn would be non-negative linear values.

Pooling Layer

Pooling layers section would reduce the number of parameters when the images are too large. Spatial pooling also called subsampling or down sampling which reduces the dimensionality of each map but retains important information.

Fully Connected Layer

The layer we call as FC layer, we flattened our matrix into vector and feed it into a fully connected layer like a neural network.

Algorithm for Data Augmentation

Step 1: Here we will do two important things

1. Resizing
2. Rescaling

Step 2: Make sure that all the images are in a particular size

Step 3: Then rescale every image using formula every image/255

Algorithm for CNN

Step 1: We need to add convolutional 2D reLu , which is used to extract common features. Here the activation function is reLu

Step 2: Then add pooling layer which takes only maximum features

Step 3: Now add flatten layer to classify images

Step 3: To connect all the layers. here we have fully connected layers

Step 4: Finally, we add the output layer, here the activation function is sigmoid

Algorithm for Training

Step 1: Initially we need to compile

Step 2: Then we need to train using adam optimizer to reduce errors

Algorithm for Testing

Step 1: We need to rescale and resize the image.

Step 2: Load the image with target size and convert into the array.

Step 3: Finally expand its dimensions

Proposed system

- In proposed system, there is availability of vast quality of image data using data augmentation.
- Using Convolutional Neural Network algorithm, recognition of smoke and fire images could be done with high accuracy.
- Presence of hidden layers helps to extract desired features from the image.
- This improves the performance of the network.

Output screens

Figure 3 Fire image

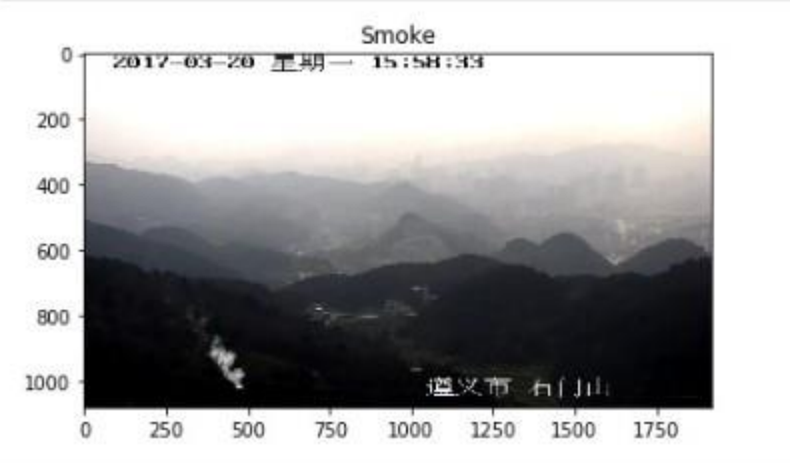

Figure 4 Smoke image

Conclusion

In this paper, we showed that very high classification performance can be achieved using deep CNN'S even when limited data is provided. The over fitting problem caused by a limited set of images data for training, leads to poor performance in neural network models. To solve this problem, we enlarge our training sets using various data augmentation parameters. In future current work can be extended and develop a robust fire and smoke detection algorithm capable of pinpointing the location of fire and smoke

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