LITERATURE SURVEY

1. Introduction

Fire detection is one of the essential modules in an early warning system, which is used to identify abnormal events in a monitoring area. Fire detectors are used to provide the earliest possible warning of a fire. Conventional fire detectors currently use smoke and temperature sensors. If the sensor is placed in an open and wide area such as a forest, densely populated settlements, and roads, it will be less effective and cost a significant amount of money. In addition, conventional fire detectors have problems regarding delays and alarm sound errors. In other words, the utilization of camera monitoring is currently increasing to ensure citizens' safety. Therefore, it is possible for Closed Circuit Television (CCTV) cameras to detect fires using digital image processing and computer vision technology, referred to as image-based fire detection. The advantages of image-based fire detection compared to conventional fire detectors can be placed in an open and wide area so that the costs incurred can be cheaper.

Image-based fire detection is strongly influenced by the features used to distinguish fire from other objects. Two types of features are often used to detect fire: handcrafted features and non-handcrafted features. Handcrafted features are designed with predetermined rules. Examples of these features are motion, shape, color, and texture. Meanwhile, non-handcrafted features are obtained directly from the neural network layers.

Several recent studies have used non-handcrafted features for fire detection. For example the deep learning architecture used is a Convolutional Neural Network (CNN), while uses Squeeze Net. Deep learning architecture is also used to overcome the problem of few data, as was done by implementing the Generative Adversarial Network (GAN).

2. The Proposed Framework

The fire detection system starts by forming a color probability model for the segmenting fire region. Then, the model is trained based on a dataset containing varying fire colors. This model would find the fire region candidates in the video frames extracted from the video input. After obtaining the candidates, the machine learning strategies were performed for verifying them based on the color histogram . This research utilized two machine learning methods: support vector machine (SVM) and random forest (RF). SVM is used because of its ability to classify an object into two classes linearly. On the other hand, RF was chosen because of its ability to combine color and motion features in object classification. However, these two methods will be compared in implementation to obtain the most optimal framework. Lastly, further verification was then conducted by checking the motion of fire regions. The fire motion was measured according to the centroid and the area of the region. If the method detects irregular motion in a fire region, then this region was assigned as a fire object and vice versa.

2.1. Training Data Acquisition

In this research, two training datasets were used: the dataset for fire segmentation and fire classification. The dataset for segmentation consisted of 30 images of fire regions in various conditions with the size of 100 × 100 pixels. The features were extracted on this dataset based on the RGB color model for representing the variation in fire colors in the color probability model. On the other hand, the fire classification stage utilized a dataset consisting of 1124 fire images and 1301 non-fire images created by Jadon et al. . It was produced by capturing photographs of fire and non-fire objects in challenging situations, such as the fire image in the forest and non-fire images with fire-like objects in the background. The dataset was then divided into 80% and 20% for training and testing subsets.

2.2. Motion Feature Analysis

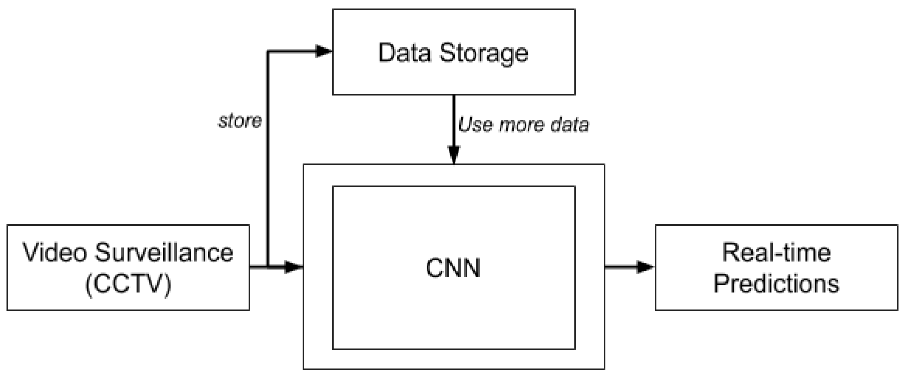
Verifying a fire region based solely on the color feature may produce some false positives, e.g., a red-colored non-fire object is classified as a fire object. Besides color, another characteristic of fire is its irregular movement in certain areas. Therefore, a further verification stage was conducted by utilizing the motion feature to reduce false positives. The object motion could be represented by image moments. Thus, the image moments, particularly the centroid and the area, were exploited in the experiment

2.3 Image Processing

Image processing is the process of manipulating images using computers and operates on images to extract the data or the information and execute some tasks from the related images.A digital image is an array of the real and complex numbers represented by a finite number of bits. Digital image processing can be referred to as a numerical representation of the object to perform a series of operations by using different algorithms to get the desired output. With the development of image processing technology, it is used in various core research and development programs such as forest fire detection system

2.4 Convolutional Neural Network

Convolutional Neural Network has become really popular for image classification since the LeNet [16] performed well on the MNIST Data (Hand written Digits Dataset) and achieved an accuracy which is more than humans. Since then, CNN has performed at a state-of the-art level at image classification tasks.



A typical CNN consists of different types of processing layers including convolution, pooling, and fully connected. These layers are arranged in such a way that the output of one layer becomes the input of the next layer. At each convolution layer, a number of kernels are applied to the input data to generate feature maps. Pooling layers select maximum activations within small neighborhoods of these features maps to reduce and introduce translation invariance. Fully connected layers followed by stacks of convolutional and pooling layers model high-level abstractions in the data and serve as high-level representations of the input. The weights of all the convolutional kernels and neurons in the fully connected layers are learned during the training process and correspond to essential characteristics of the training data, useful for performing the intended classification

3.METHODOLGY

For the implementation part of the paper, Python has been used extensively. With its relatively easy learning curve and many open-source Machine Learning Frameworks, Python was used in experimenting and prototyping. Out of the many Machine Learning Frameworks, Keras was chosen due to the availability of many pre-trained models. Google Colab, is a research tool for machine learning education and research developed by Google. It's a Jupyter notebook environment that comes with pre-installed Machine Learning tools and libraries. And it is also free to use for research purposes. The dataset has been loaded into Google Colab, pre-processed, split into training, validation and testing set, then used for training pretrained models and then tested. As the project is based mostly on Python, Matplotlib library is used for data visualization. A. Preprocessing The mivia dataset is downloaded and loaded into Google Colab. The dataset comprises of 31 videos with 14 fire videos and 17 non-fire videos. Using OpenCV library, the video frames has been split into images and stored in respective labeled directories. The data in these labels are further split into training, validation and testing datasets. One of the standard ratios was used, 60% for training, 20% for validation and 20% for testing.

CONCLUSION

This method of processing capabilities of smart devices has shown promising results in surveillance systems for the identification of fire accidents. Fire is one of the most dangerous events which can result in great losses if it is not controlled on time. This necessitates the importance of developing early fire detection systems. Therefore, in this paper, we used a cost-effective fire detection CNN architecture for surveillance videos. The model is inspired by GoogleNet architecture and is fine-tuned with a special focus on computational complexity and detection accuracy. It is proved that the proposed architecture dominates the existing hand-crafted features based fire detection methods which rely on basic image processing techniques.

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