Fire Detection System based on CNN

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Abstract— The embedded processing have enabled the vision based systems to detect fire during surveillance based on convolutional neural networks (CNNs).The proposed method for a cost-effective fire detection CNN architecture for surveillance videos. The model is inspired for GoogleNet architecture. The fire are features are extracting the super pixel method. Its computational complexity and suitability for the intended problem compared to other computationally networks. When balanced the efficiency and accuracy. The nature of the problems and fire data. The Experimental results helpful for fire datasets reveal the effectiveness of the proposed framework and its suitability for fire detection in CCTV surveillance systems compared to another fire detection methods.

Keywords: Convolutional Neural Network, Fire Detection, Image Classification, Real-World Applications, Deep Learning, and CCTV Video Analysis

I. INTRODUCTION

Deep learning algorithms can perform humans at classifying images. It's achieving levels of accuracy to the point where deep learning algorithms can outperform humans at classifying images. The embedded capabilities of devices have resulted in good surveillance. That providing a number of helpful applications in different type such that e-health, autonomous driving, and event monitoring. Digital image processing is the use of computer algorithms to perform image processing on digital images. Fire is one of the dangerous events which can result in great losses if it is not controlled at a time. The importance of developing early fire detection systems. The cost-effective fire detection CNN architecture based on surveillance videos .fire is one of the commonly happening events, whose detection at early stages during surveillance can avoid fire disasters

II. MOTIVATION

fire is one of the commonly happening events, that detection at early stages during surveillance can avoid and fire disasters. Other fatal factors of home fires, physical disability is the secondly ranked factor which affected 15% of the home firevictimsdelayedescapefordisabledpeopleasthetraditionalfi realarmingsystems.Thestrong fires or close proximity, failing to generate an alarm on time for such people. It's achieving unprecedented levels of accuracy to the point where deep learning algorithms can outperform humans at classifying images. The embedded processing capabilities of good devices have resulted in smart surveillance. That providing a number of helpful applications in different type of domains such that e-health, autonomous driving, and event monitoring. The digital image processing is the useful of computer algorithms to perform image processing by the digital images. The fire detection using hospital, schools, city etc. It help to detecting fire. The covalution network identifying fire or not fire. This will enable the video surveillance systems to handle more complex situations in real-world.

III. LITERATURE SURVEY

Khan Muhammad Hu et al. [1] propose a secure surveillance framework for IoT systems by intelligent integration of video summarization and image encryption. An accurate video summarization method is useful to extract the informative frames using the processing capabilities of visual sensor. The detected from key frames, an alert is sent to the concerned authority automatically. When the final decision about an event mainly depends up on the extracted key frames, The modification during transmission by attackers can result in severe losses. The issue was propose a efficient probabilistic and lightweight algorithm for the encryption of key frames prior to the transmission, considering the memory and processing requirements of constrained devices which increase its suitability for IoT systems. Our experimental results verify the effectiveness of the proposed method in terms of robustness, execution time, and security compared to other image encryption algorithms. The framework can decreases the bandwidth, transmission cost, storage and the time required for analysts to browse large volumes of surveillance data and make decisions about abnormal events such as suspicious activity detection and fire detection in surveillance applications

JongwonChoietet al.[2] propose Fire detection is one of the most interesting issues for surveillance. The another approaches for the fire detection suffer from a very high false positive ratio. To solve the problems, the present a patch-based fire detection algorithm with online outlier learning. In the proposed algorithm, the candidates of fire are obtained in the form of patch, while the classical candidates have been based on pixels or blobs. Because the patches of fire have more distinctive shape than the original fire, the shape classifier can recognize the candidates correctly from fire-like outliers. In addition, I propose an online outlier learning scheme which handles the irregularity of fire based on the repeatability of shape in time. The first step is to extract the distinctive patches from the all image to minimize the computational complexity. In the second step, the descriptors are obtained for the candidate patches and, for the third step, The remove the candidates that are rejected by the shape appearance classifier. In fourth step, a randomness classifier checking the repeatability of the classified descriptors by an online outlier learning scheme and rejected the fire-like outliers. In the last step, The determine a fire alarm by thresholding the detection map obtained from the positions of the remaining candidates by using spatio-temporal filter. The proposed the patch-based fire detection with the online outlier learning scheme. The next contribution is to introduce the online outlier learning scheme, which identifies the irregularity of the candidates by matching them to the words of the online outlier dictionary. The experiments that the approach distinguished the candidates qualitatively and decided the fire alarm quantitatively.

Ali Rafieeet al.[3] propose the fire and smoke monitoring systems are helpful in different industry such that military, social security and economical. The methods for fire and smoke detection are used only motion and color characteristics this many wrong alarms are happent and this is decrease the performance by the systems. This research presents a newly method for fire and smoke detection through image processing. In this algorithm all objects in an image is considered and then checking them to figure out which objects are smoke and fire. The color, motion of fire and disorder are helpful characteristics in fire and smoke detection algorithm. Smoke of fire will be the whole or part of the images. Thus by processing of the video frames, different objects will detect. The result of evaluate the features of objects, the goal objects (fire and smoke) can be defined easily. Two-dimensional wavelet analysis is used in the presented method. The results of this research present the proposed features that can decrease the wrong alarms and increase the system performances. The new method for detecting the smoke and fire in video images. The objects were detected, and then removed the objects, which did not have the fire or smoke properties. Its detecting the color of each objects. The proposed method used the dynamic and static characteristics related to the smoke and fire. The two-dimensional wavelet analysis is a static characteristic.

Yusuf HakanHabibo et al.[4] proposed The proposes a video-based fire detection system uses color, spatial and temporal information. The system separate the video into spatio-temporal blocks and uses covariance-based features extracted from these blocks to detect fire. Feature vectors take advantage of both the spatial and the temporal characteristics of flame-colored position. The extracted features are trained and tested using a support vector machine (SVM) classifier. The system does not use a background subtraction method to segment moving regions and can be used, to the some extent, with non-stationary cameras. In addition, it is shown that perform a another method in terms of detection performance. The real-time video fire detection system is developed based on the covariance texture representation method. The covariance method is ideally suited for flame detection for two reasons: flames exhibit random behaviour, and another it is experimentally observed that the underlying random process can be considered to the wide sense stationary process for a small video region. The second order statistical modeling using the covariance method provides a good solution to flame detection in video. The proposed method is computationally efficient and can process 320 × 240 frames at 20 fps in an ordinary computer size. The main contribution of this system is the use of temporal covariance information in the decision process. Most fire detection methods use color, spatial and temporal information separately, but in this work use temporally extended covariance matrices in order to use all the information together. When this method for fire is clearly visible.

Turgayelik et al.[5] proposed Fire detection in video sequences using a generic color model. A rule-based generic color model for flame pixel classification is performed. The proposed algorithm uses YCbCr color space to divides the luminance from the chrominance more effectively than color spaces such as RGB or rgb. The performance of the proposed algorithm is tested on two classes of images, one of which contains fire, the other containing fire-like regions or objects. This method achieves up to 99% fire detection rate. The number of arithmetic operations for the proposed color model is linear with image size and algorithm is very low in computational complexity. This makes it suitable for the real-time applications. The color model can be used in fire detection in video sequences. I have shown that the proposed algorithm performs very well in segmenting fire regions in video sequences. In our future work, the will make the time analysis of fire regions in video sequence by measuring or evaluating spread in the fire regions. Furthermore, the flicker nature of fire will be considered as a future work. The method uses statistical features, based on grayscale video frames, including mean pixel intensity, standard deviation, and second-order moments, along with non-image features such that humidity and temperature to detect fire in the cargo compartment. The system is commercially used in parallel to standard smoke detectors to minimize the false alarms caused by the smoke detectors.

IV. PROPOSED SYSTEM

Majority of the research the last decade is focused on traditional method of features extraction for flame detection. The major issues with such methods is their time consuming process of features engineering and their low performance for flame detection. Each methods also generate large number of false alarms mainly in surveillance with shadows, varying lightings, and fire-colored objects. To cope with such issues, we extensively studied and explored deep learning architectures for early flame detection. Motivated by the recent improvements in embedded processing capabilities and potential of deep features, we investigated numerous CNNs to improve the flame detection accuracy and minimize the false warnings rate. An overview of our framework for flame detection in CCTV surveillance networks. Fire is one of the 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. The cost-effective fire detection CNN architecture for surveillance videos. The video are transferred to video frames based on the image processing. When frames are input to the CNN network. The network identifying fire or non-fire. CNN is fire classified based on the fire features such as color, shape, motion and distance of the fire. The distance measuring using infrared cameras. The system performance will be increasing using the regression filter. When the system to identifying the fire feature using color, shape, motion and distance of fire. It use the infrared cameras.

V. SYSTEM ARCHITECTURE

CNN is a framework of deep learning which is inspired from the mechanism of visual perception of living creatures. Since the first well-known DL architecture LeNet for hand-written digits classification, it has shown promising results for combating different problems including action recognition, pose estimation, image classification, visual saliency detection, object tracking, image segmentation, scene labeling, object localization, indexing and retrieval, and speech processing. Among these application domains, CNNs have extensively been used in image classification, achieving encouraging classification accuracy over large-scale datasets compared to hand-engineered features based methods. The main factor is their potential of learning rich features from raw . A Convolutional Neural Network (CNN) is a type of feed-forward artificial neural network where the individual neurons are tiled in such a way that they respond to overlapping regions in the visual field. These neurons are sensitive to small sub-regions of the visual field, called a receptive field. The sub-regions are tiled to cover the entire visual field. These neurons work as local filters over the input space and are well-suited to exploit spatially local correlation presented in natural images. One of the main contributions of CNN on neural network area is the implementation of weights sharing, applying same weights on same feature map, which increases the learning efficiency by significantly reducing the number of trainable parameters. Then, in recent years, active functions and dropout algorithm were implemented on CNN, which increases the non-linearity and independence of feature maps, then leads to higher-understanding and more stable learnt features.

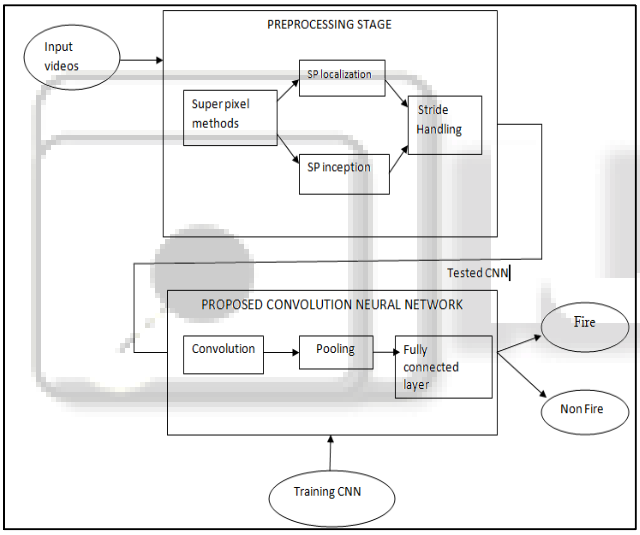

Fig. 1: Architecture Diagram

There are two fundamental layer types in a CNN: convolutional layers and pooling layers. And with the development of CNN, active functions, dropout is added in order to increase the performance of CNN. And in the last layer of CNN, different loss layers are chose according to the type of tasks.

VI. Methodology

A. *Technologies*

1) *Convolutional Neural Network:*

Convolutional layer is a core building block of CNN, which differs CNN with traditional artificial neural networks. To avoid the situation of learning billions of parameters (if all layers are fully connected), the idea of using convolutional operations on small regions has been introduced. One major advantage of convolutional networks is the weights sharing in convolutional layers, which means implementing same filters on same feature map. Weights sharing helps to reduce the required computing memory and to improve CNN performance on computer vision tasks. Fig.3.2 shows the weights sharing's effect on parameter reduction. Then, by reducing the number of trainable parameters, the over-fitting problem of traditional neural network was alleviated. The parameters of convolutional layer consist of a set of learnable filters, which is small spatially. During the forward pass, each filter is convolved across the width and height of the input volume, producing a 2-dimensional activation map of that filter. The network learns filters that will be activated by specific types of features from the input at certain positions, which is same with the convolutional operation in the traditional feature designed algorithms - extracting basic features from inputs. Then, stacking these activation maps for all filters along the depth dimension forms the full output volume. With the help of weights sharing, the number of learnt filters in convolutional increased, which enables the extraction of more information from input data.

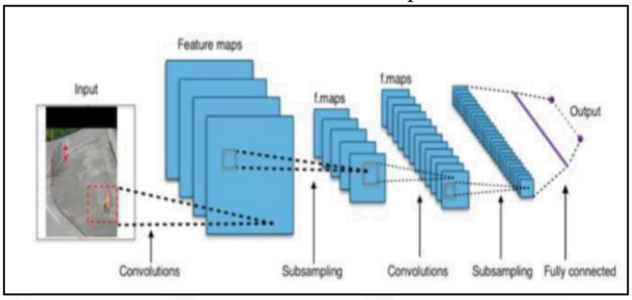

Fig. 2: Main operations of a typical CNN architecture.

2) *Super Pixel Method*

Graph-based method to superpixel generation treat each of the pixel as a node in a graph. Edge weights between two nodes are proportional to the similar to the neighboring pixels or cells. Superpixels are created by minimizing a cost function defined over the graph. An image is covered with overlapping square patches of fixed size, left. Each pixel are covered by several patches, and the task or feature is to assign a pixel to one of them. If two neighboring pixels are focusing to the same patch, there is no penalty. If they are to different patches, then there is a stitching penalty that is inversely proportional to the intensity difference to the pixels. Intuitively, we are stitching patches so that can seams are encouraged to align with intensity edges. The stitching result is in Figure 1, middle, and superpixel boundaries are in right. Boundaries are regularized due to the stitching energy function. A superpixel not be too large, not larger than a patch size. Small superpixels are discouraged because they contribute a large cost to the stitching energy.

B. *Algorithms*

1) *SLIC*

Superpixels are the increasingly famous for use in computer vision applications. However, there are some algorithms that output a desired number of regular, compact superpixels with a low computational overhead.I introduce a novel algorithm called SLIC (Simple Linear Iterative Clustering) that clusters pixels in the combined five-dimensional color and image plane space to egenerate compact, nearly uniform superpixels. The simplicity of the approach makes it extremely easy to use – a lone parameter specifies the number of superpixels – and the efficiency of the algorithm makes it very practical. Experiments show to the approach produces superpixels at a minimum computational cost while achieving a segmentation quality equal to or greater than four state-of-the-art methods, as measured by boundary recall and under-segmentation error. We also demonstrate the benefits of our superpixel approach contrast to previous methods for different tasks in which superpixels have already been shown to increase performance over pixel-based methods.

2) Pooling

It is common to periodically insert a Pooling layer in-between successive Convolutional layers in a ConvNet architecture. The function is to progressively minimize the spatial size of the representation to minimize the amount of parameters and computation in the network, and hence to also control over fitting. The Pooling Layer operates independently on every depth slice of the input and change size it spatially, using the MAX operation. The most common form is a pooling layer with filters or reduce of size 2x2 applied with a stride of 2 down samples depth slice in the input activation. Every MAX operation would in this case be taking a max over 4 numbers (little 2x 2 regions in some depth slice). The depth dimension remains unchanged.

3) Dropout

A CNN architecture contains multiple non-linear hidden layers, which makes CNN as expressive model that is able to learn the complicated relationships between the inputs and outputs. However, under the situation where there is limited training data, many of these complicated relationships will be the result of sampling noise, which only exists in the training set but not in test data, even if the testing data is drawn from the same distribution. Then, over fitting would occur during training process. Many methods have been developed to reduce such issue, such as stopping the training as soon as performance on a validation set starts to get worse, introducing various kinds of weights penalties and soft weight sharing. Dropout is a powerful algorithm introduced to solve the over fitting problem, which reduces the generalization error of large neural networks. It reduces complex co-adaptations of neurons, since in dropout algorithm a single neuron cannot rely on the presence of other neurons. Dropout, therefore, enhances CNN to be able to learn more robust features and stable structure By dropping a unit out, that mean temporarily removing it from the network, along with its all connections. Dropout can be interpreted as a method to regularize a CNN by adding noise to its hidden units. The idea of adding noise to the states of units has previously been used in the context of Denoising Auto-encoders (DAEs), where noise is added to the input units of the network is trained to reconstruct the noise-free input. However, different from DAEs in training process, dropout can be used in all layers except loss layer and occurs during supervised training with end-to-end back-propagation. At testing time, it isnot practical to take average of the predictions from models with all dropout situations occurred in training process. A simple approximate averaging method is implemented to solve this problem and works well. The idea is to use the trained network 16 without dropout at testing time. The weights of the network are scaled-down versions of different the trained weights.

4) Fully-Connected

Neurons are the fully connected layer have full connections to all activations in the previous layer, as seen in natural Neural Networks. Their activations can be computed with a matrix multiplication followed by a bias in offset. Finally, after several convolutional and max pooling via fully connected layers. A fully connected layer takes all neurons in the previous layer (be it fully connected, pooling, or convolutional) and connects it to every single neuron it has. Fully connected layers are not spatially located anymore (it can visualize as one-dimensional), so there can be no convolutional layers after a fully connected layer.

VII. Result

The dataset has been made challenging for both color-based and motion-based fire detection methods by capturing videos of fire-like objects and mountains with smoke and clouds. This is one of the motivations for selection of this dataset for our experiment. The results are comparing with other flame detecting methods, which are carefully selected using a selection criteria, reflecting the features used for fire detection, time, and dataset. The best results are reported by among the existing recent methods by achieving an accuracy of 93.55% with 11.67% false alarms.

Fig. 2: Input video frame

The score of false alarms is still high and needs further improvement. Therefore, we explored deep learning architectures (AlexNet and GoogleNet) for this purpose. The results of AlexNet for fire detection are taken from our recent work. Initially, we trained GoogleNet model with its default kernel weights which resulted in an accuracy of 88.41% with false positives score of 0.11%.

Fig. 3: Segmented image

The finalized an optimal architecture, having the potential to detect flame in both indoor and outdoor surveillance videos with promising accuracy. For getting inference from the target model, the test image is given as an input and passed through its architecture. The output is probabilities for two classes i.e., fire and non-fire. The maximum probability score between the two classes is taken. The recent improved processing capabilities of smart devices have shown promising results in surveillance systems for identification of different abnormal events i.e., fire, accidents, and other emergencies.

Fig. 4: Fire image

Fire is one of the 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 research article, we propose a cost-effective fire detection CNN architecture for surveillance video

VIII. Conclusion

In this paper recent works in the field of fire detection was discussed. Many researchers had contributed and are still working in this field. This field to processing capabilities of accurate devices have shown promising results in surveillance systems for identification of different abnormal events such as fire, accidents, and other emergencies. Fire is one of the dangerous events that result can be great losses if it is not controlled at a time. This necessitates to importance of developing early fire detection method. When propose a cost-effective fire detection CNN architecture for surveillance videos. The model is inspire to GoogleNet architecture and is fine-tuned with special focus on computational complexity and detection accuracy. The proved that the proposed architecture dominates the existing hand-crafted features based fire detection methods as well as the AlexNet architecture based fire detection method. Although, when the improved the flame detection accuracy, yet the number of false alarms is still high and further research is required in this direction. The flame detection frameworks can be intelligently tuned for detecting of both smoke and fire. This video surveillance systems to handle more complex situations inreal-world.

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