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Early fire detection technique for human being using deep learning algorithm

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ABSTRACT

Fire and smoke detection in today's world is a must, especially in clustered areas where a quick response can prevent significant damages and save lives. Early detection plays a significant role in preventing the fire from spreading by alerting the emergency response personnel. It may not be possible to install traditional fire and smoke detectors everywhere. As a result, incorporating fire and smoke detection into existing closed circuit television (CCTV) systems in various places can provide a warning to the appropriate authorities, allowing for quick action to prevent the fire from spreading. This work aims in developing an early fire and smoke prediction model with CCTV footage images and video frames. The images and videos are collected from multiple datasets available online. A convolutional neural network (CNN) model is developed for early detection and prevention of the spreading of fire and compares it with transfer learning models ResNet50 and VGG19. The model obtain an accuracy of around 94% using CNN model, 95% using VGG19 and 98% using ResNet 50. A model with high accuracy can replace traditional fire detection systems which can be both cost-effective and easy to implement to existing surveillance cameras.

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1. INTRODUCTION

Fire may lead to severe damage to human life and property. In today's world, fire and smoke detection are necessary, especially in densely populated regions where a timely reaction may avoid considerable damage and save lives. It may not be possible to install traditional fire and smoke detectors everywhere. As a result, incorporating fire and smoke detection into existing closed circuit television (CCTV) systems in various places can provide a warning to the appropriate authorities, allowing for quick action to prevent the fire from spreading. When compared to traditional fire detectors, it may be more cost-effective. Early discovery helps to prevent the fire from spreading by informing emergency responders [1].

Early identification of fires can save many lives as well as save buildings and homes from serious infrastructure damage. In congested metropolitan settings, detection by local monitoring is both required and effective for achieving high accuracy and resilience. Traditional fire detection systems have a number of drawbacks, including the need for many, frequently redundant systems, fault-prone technology, routine maintenance, false alarms, and so on [2]. As a result, detecting fires via surveillance video stream is one of the most practical and cost-effective solutions for replacing old systems without requiring massive infrastructure changes and integrating it with existing CCTV cameras.

This project aim to use deep learning to create a model that can recognize fire in images or video frames, providing early detection and warning individuals of a potential fire. In surveillance films videos, this model may be used to identify fires. This, unlike traditional systems, does not need any additional specific infrastructure and is also cost-effective. As more data about fire scenes becomes accessible, the model's accuracy will increase [3].

2. LITERATURE SURVEY

2.1. Three-dimensional analysis of fire onset structures in a turbulent flame with digital imaging

This paper presents a flam detection system in gas turbines by placing similar kinds of cameras in different locations around the gas turbine and using image processing techniques for extracting features. Specialized computational algorithms have been developed to rebuild the flame front's 3-D architecture. These algorithms employ mesh generation, contour extraction, and edge recognition as methods of image processing. The different flaming characters like ignition points, volume, surface area, and circularity are predicted by the model. The outcomes produced under diverse circumstances demonstrate the system's capacity to quantitatively analyse 3-D flame front forms under a range of combustion scenarios [4]–[7].

2.2. Processing large space fire images with an adaptive smoothing-based canny edge detector

In this research, the video data from a conventional camera monitoring is used to analyse the flame area using an adaptive canny edge method and flame geometric properties. Using a modified canny operator strategy that combines fire detection with adaptive smoothing, potential fire zones were located. In order to exclude non-fire pixels, a luminance map was made because fire zones have a higher luminance contrast than their surroundings. The proposed selection criterion improves the performance of traditional canny operators. In trials, it was discovered that the suggested strategy was more noise-resistant and helped to separate the flame zones of succeeding frames.

2.3. Deep learning technique for fire detection

The authors proposed a deep neural network model for smoke and fire deduction based on images as input. The testing results are evaluated based on accuracy, deduction rate, and false alarm status as quality of service (QoS) parameters and the proposed model performs better in all aspects. The activation function used in the hidden layer usually are rectified linear units (ReLU) or tangent function, which is modified in the proposed method as an adaptive linear unit. The dataset is also created new by using real-time images collected with smoke and fire, and a few images were collected from internet websites. To avoid the over fitting issue brought on by training the network on a short dataset, they merged usual data augmentation techniques and generative adversarial network (GAN). This resulted in an increase in the number of training images that were available [5], [8], [9].

2.4. Video based early fire alert system

They provide a technique for early fire detection that can identify flames in a stream of real-time video from multiple cameras based on the Lucas-Kanade optical flow algorithm. It detects fire before it starts to burn, allowing for a speedier reaction than a traditional fire detector would allow. The technique looks for colours like fire by first using a filter to find moving pixels in the image that are being subtracted from the backdrop. The experimental results show that detecting fire-like colour, increase accuracy and decrease false alarm.

2.5. Hidden Markov models for fire detection

This article presents a novel real-time hidden Markov model (HMM)-based fire detection system. This study's main contribution is the development and application of a hidden Markov fire model that, by combining information on fire motion with state transitions between fire and non-fire, lowers data redundancy. The ultimate decision for the training supply parameters for the HMM application is made using this model, which involves both training and application. The experimental results show an increased accuracy and decreased false alarm with the tested images [10]–[13].

3. PROPOSED WORK

3.1. Convolution neural network

Convolution neural network (CNN) is a type of artificial neural network (ANN) with maximum number of hidden layers. It consists of convolutional layer, max pooling layer and fully connected layer arranged in order and these layers can be added as many times as needed. Fire detection is divided into three parts: i) data set generation, ii) building the fire detection CNN models, and iii) prediction using the model created.

3.2. Data set generation

The dataset used in this work has 1187 fire images and 1016 non-fire images. The images are collected from multiple datasets available online. Then the fire and non-fire images are separated out and distributed into their respective folders and the dataset is prepared for analysis and further processing [14]–[16].

Figure 1 represents the fire and non_fire images distribution, the data frame is created for storing the image paths and label the data accordingly as ‘fire’ and ‘non_fire’. Then it store the height and width of the images in the dataframe and visualize the height and width of the images. As the images are of variable heights and widths, we need to resize the images to a standard size. Then two generators are constructed to train generator and validation generator for training and validation respectively. The data prepared can be used as an input to the training model. Figures 2 and 3 denotes the sample fire images used for training [17]–[19].

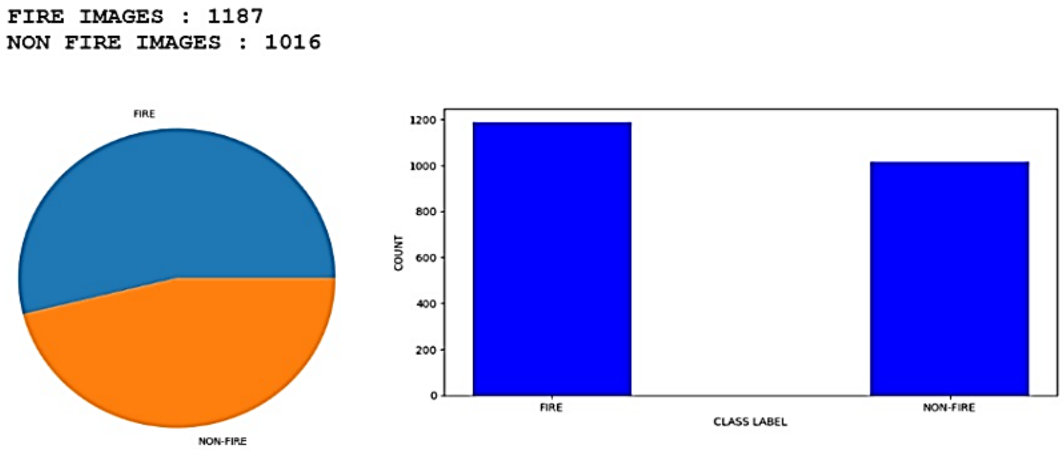

Figure 1. Fire and non_fire images distribution

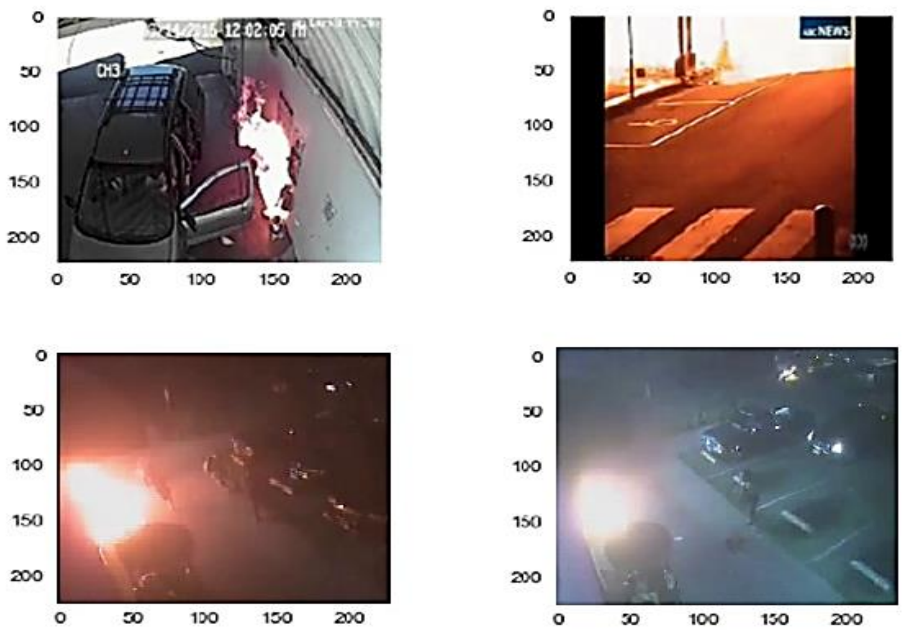

Figure 2. Sample fire images used for training

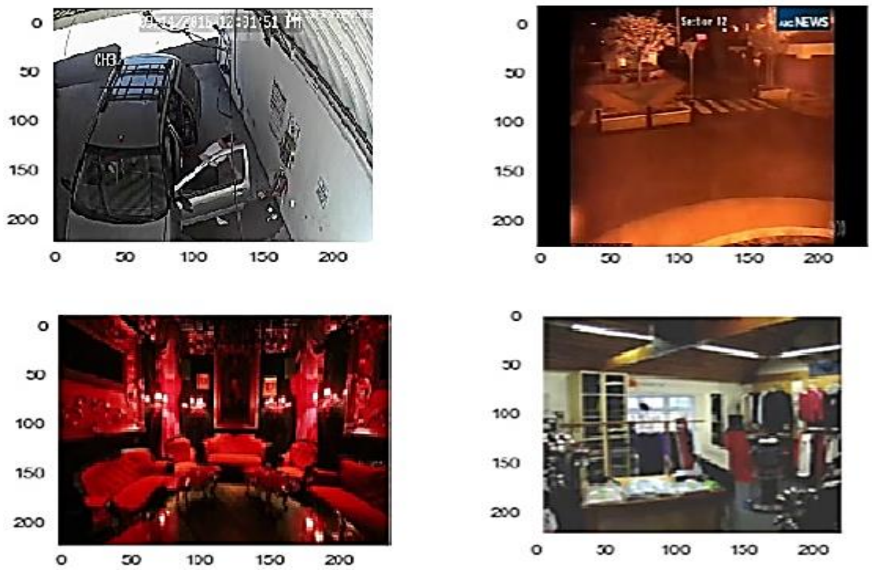

Figure 3. Sample non-fire images used for training

3.3. CNN model

The model consists of three convolutional layers followed by pooling layer is used. It is followed by three densely connected layers. First convolutional layer takes the image of size 224×224 and process with 32 filters of size 3×3 using ReLU activation function. Second convolutional layer use 64 filters and third convolutional layer used 128 filters. For this application Max pooling layer is used for convergence [20]–[23].

3.4. Activation function and optimizer

The activation function used by all convolutional layer is ReLu, since it is going to output either zero or maximum value of the pixel. For dense layer, fully connected layer the activation function used is Sigmoidal Activation to predict the percentage of belongingness for each class labels. Optimization is the process of modifying the weights and learnable parameters of ANN links. This helps in increasing accuracy and decreasing loss values. The optimizer used for this work is Adam optimizer. Adaptive gradient algorithm (ADAGRAD) and root mean square propagation, two extensions of two stochastic gradient descent techniques, are combined by Adam (RMSProp).

3.5. Transfer learning models

Transfer learning is the process of using the existing trained model for feature extraction. This acts as the starting point in image classification models [24], [25]. This is then followed by ANN structures for the classification process. The most commonly used pre-trained models are VGG and ResNet. For this work, ResNet50 and VGG19 are used to evaluate the accuracy of prediction.

A popular deep learning model called residual networks (ResNet) is the cornerstone of several image classification tasks. ResNet changed the game because it made it possible for us to efficiently train extremely deep neural networks with more than 150 layers. Prior to ResNet, it was challenging to train very deep neural networks. ResNet has a lot greater depth than VGG16 and VGG19, but the model size is substantially smaller since fully-connected layers aren't used; instead, global average pooling is used. This work employs ResNet-50, a deep convolutional neural network with 50 layers.

A variation of the VGG model called VGG19 has 19 layers in total (16 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer). VGG19 is a 19-layer version of VGG (16 convolution layers, 3 fully linked layers, 5 MaxPool layers, and 1 SoftMax layer). In a paper released in 2014, Simonyan and Zisserman revealed the VGG network architecture. Prior AlexNet derivatives focused on smaller window widths and advancements in the first convolutional layer, whereas VGG handles a key aspect of CNNs, namely depth.

4. RESULTS AND DISCUSSIONS

The images are loaded using image.load_img. The images are resized to 224×224. After pre-processing the input images were passed into the proposed CNN and pre trained models for training and testing. The classification output is categories as ‘0’ or ‘1’. If the category is found out to be ‘0’, the image contains fire, otherwise if it is '1' the image does not contain fire. For the identification of fire in photos, the suggested study employs both CNN and deep CNNs with transfer learning. Then the performance of the CNN models were compared, mainly ResNet50 model and VGG19 model. In accordance with epochs, the relevant accuracy and loss graphs were plotted. Fire detection performance is compared to classic CNN versus two deep learning models, VGG19 and ResNet50, which use transfer learning to improve accuracy. We obtain an accuracy of around 94% using CNN model, 95% using VGG19 and 98% using ResNet50, which is witness in the Figure 4. As Loss vs. Epochs of CNN model, Figure 5. Denotes the Accuracy vs. Epochs of CNN Model, Figure 6 represents the Loss vs. Epochs of VGG19, model, Figure 7 Represents Accuracy vs. Epochs of VGG19 picture, Figures 8 and 9. Represents Loss vs Epochs of ResNet50, model and Figures 10 and 11 denotes the predicted label is: fire, the above said comparison, graph and picture represents the valuable evidence that the proposed model is very efficiency in the early perdition of fire so safe the human life.

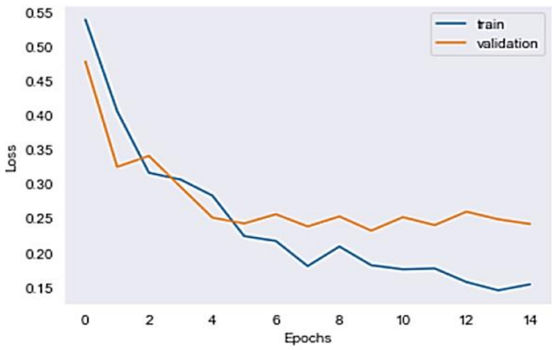

Figure 4. Loss vs Epochs of CNN model

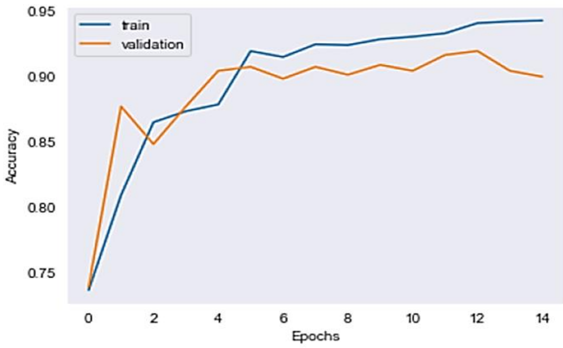

Figure 5. Accuracy vs Epochs of CNN model

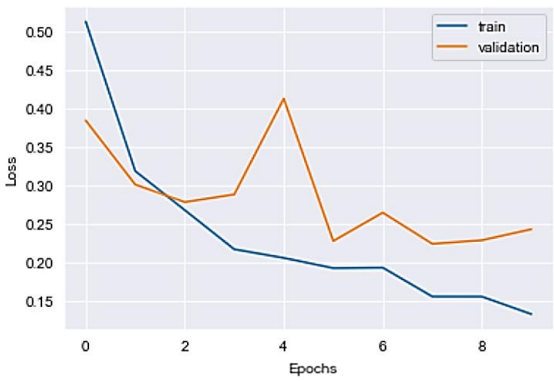

Figure 6. Loss vs Epochs of VGG19

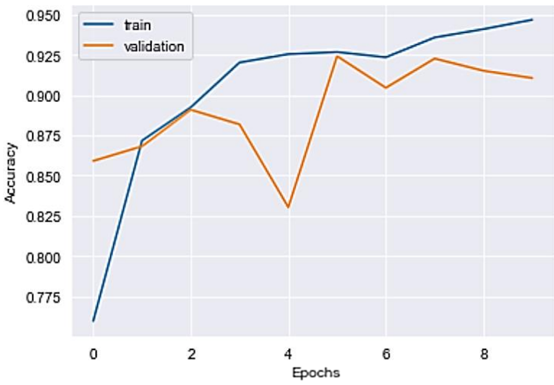

Figure 7. Accuracy vs Epochs of VGG19

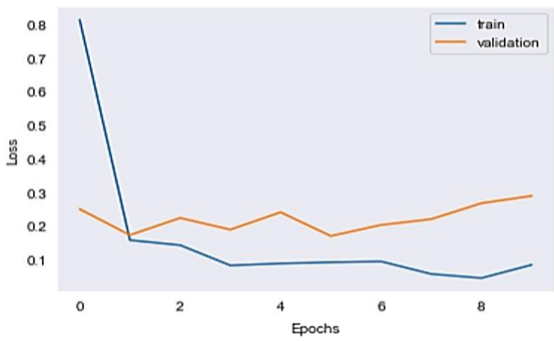

Figure 8. Loss vs Epochs of ResNet50

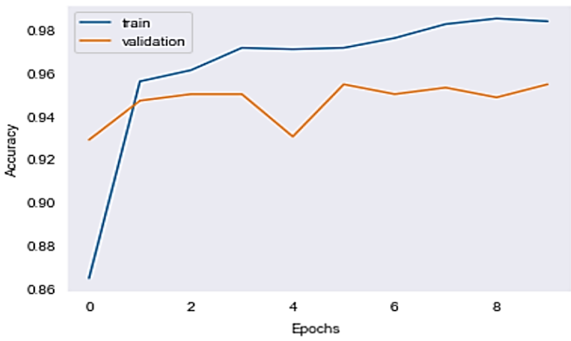

Figure 9. Loss vs Epochs of ResNet50

Figure 10. Predicted label is: fire

Figure 11. Predicted label is: non_fire

5. CONCLUSION

In the modern world, fire and smoke detection are essential, especially in densely populated places where an immediate response can limit serious damage and save lives. The accuracy of the pre trained model is more compared to that CNN model since the deep layers of neurons. The model's accuracy can be improved much more. Due to the numerous parameters required to fine-tune convolutional neural networks, considerable amounts of data are typically needed for training these networks. The accuracy of the model can also be improved by adding more images.

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