AUTOMATIC DETECTION OF FIRE AND ACCIDENT PIXELS USING TENSORFLOW TECHNOLOGIES

Sri Ram Polisetty[1], Saikumar Itraju [2], Harshini VSS [3], Pavan Kumar K [4], Hari Krishna V[5]
[1,2,3,4,5] CSE, Faculty of Engineering, Godavari Institute of Engineering and Technology(A), Rajahmundry, A.P, INDIA.

Abstract: In the present scenario human requires security services like hospital, police and fire services. These services mainly depend on the human intervention. Without human interaction these services will not respond automatically. Due to lack of quick human interaction, cost of damage increases. In order to reduce the damage, we co-ordinate these services through Artificial Intelligence. Based on the intensity of the damage, photographs and exact location is sent to the respective departments. In this work, we investigate the automatic detection of fire pixel, accidents, and Illegal threat regions in video imagery within real-time bounds without reliance on temporal scene information. As an addition to previous work in the arena, we deliberate the performance of experimentally defined, reduced complexity deep convolutional neural network (CNN) architectures for this task. Opposed to modern trends in the field, our work demonstrates utmost accuracy for entire image binary fire detection, with maximum accuracy within our super pixel localization framework can be attained, via a network architecture of considerably reduced complexity. We show the relative performance accomplished in contradiction of prior work using standard datasets to demonstrate maximally strong real-time fire pixel, accidents, and Illegal threat region detection.

.***Index Terms - Artificial Intelligence, pixel, convolutional neural network, super pixel localization framework, datasets.***

I. INTRODUCTION

The upgraded embedded processing capabilities of smart devices have resulted in smarter surveillance, providing plethora of beneficial applications in various domains such as e-health, autonomous driving, and event monitoring [1]. During surveillance, different unusual events can arise such as fire, accidents, disaster, medical emergency, fight, and flood about which getting quick information is important. This can greatly reduce the chances of occurring big disasters and can control a typical event on time with the comparatively minimum possible loss. Among such unusual events, fire, road accidents are most occurring events, whose detection at early stages during surveillance can escape from tragedies [2].The National Crime Record Bureau specifies that overall 112961 people lost their lives due to fire Accidents from 2010 to 2014. This is average of 62 deaths a day. As per the newest records, in 2017, a total of 4, 64,910 road accidents were stated in the country, claiming 1, 47,913 lives and affecting injuries to 4, 70,975 persons, which turns into 405 deaths and 1,290 injuries every day from 1,274 accidents. One of the main reasons is the delayed escape for disabled people as the traditional fire alarming systems need strong fires or close proximity, and no system available for detect live accidents on roads failing to produce an alarm on time for such people. This requires the presence of effective fire alarming systems and accident detection on road for surveillance. To date, most of the fire alarm systems are technologically advanced based on vision sensors, considering its reasonably priced cost and installation. As a result, the majority of the research is conducted for fire, accident detection using cameras. Bearing in mind the above motivation, we broadly studied convolutional neural networks (CNN) for flame detection at early stages in CCTV surveillance videos.

1. Considering the restrictions of outdated hand-engineering methods, we extensively studied deep learning (DL) architectures for this problem and proposed a cost-effective CNN framework for flame detection in CCTV surveillance videos. Our framework avoids the tedious and time-consuming process of feature engineering and by design learns rich features from raw fire, accident data [3].
2. Motivated from transfer learning strategies, we practiced and modified a model with architecture related to GoogleNet for fire detection, which effectively controlled traditional fire detection schemes [3].
3. The proposed framework balances the fire, accident detection accuracy, and computational complexity as well as reduces the number of false cautions compared to state-of-the-art fire, accident and robbery detection schemes. Hence, our scheme is more suitable for early flame, accident and robbery detection during surveillance to avoid massive disasters [3].

1.1. Artificial Intelligence

Artificial intelligence (AI) is the ability of a computer program or a machine to think and learn. It is also a field of study which attempts to make computers "smart". They work on their own without being encrypted with commands. John McCarthy introduced the name "artificial intelligence" in 1955. A perfect Artificial intelligent machine is a flexible negotiator which notices its atmosphere and takes actions to get the best out of its chance of success at some goal or objective. As machines become increasingly capable, mental facilities once thought to require intelligence are unconcerned from the explanation. At present we use the AI for effectively understanding human speech, opposing at a high level in tactical game systems, self-driving cars, and interpreting complex data. It involves many different fields like computer science, mathematics, linguistics, psychology, neuroscience, and philosophy. Eventually, researchers hope to create a "general artificial intelligence" which can solve many problems as an alternative of focusing on just one. Researchers are also trying to create creative and emotional AI which can possibly understand or create art.

1.2. Deep Learning

Deep learning (also known as deep structured learning or hierarchical learning) is part of a wide-ranging family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised. Deep learning architectures such as deep neural networks, deep belief networks and recurrent neural networks have been applied to fields together with computer vision, speech recognition, natural language processing, audio recognition, social network purifying, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have created results corresponding to and in some cases superior to human specialists.

II. LITERATURE SURVEY

The available literature dictates that flame detection using visible light camera is the generally used fire detection method, which has three classifications including pixel-level, blob-level, and patch-level methods [4-5]. The pixel-level methods, are fast due to the usage of pixel-wise features such as colors and flickers, however, their presentation is not eye-catching as such methods can be easily biased. Paralleled to pixel-level methods, blob-level flame detection methods [5] show well performance as such methods consider blob-level candidates for features extraction to identify the flame. The major problem with such methods is the trouble in training their classifiers due to plentiful shapes of fire blobs. Patch-level algorithms [7-8], are technologically advanced to development the performance of the preceding two categories of flame detection algorithms, however, such methods end result in several outliers, troubling their accuracy.

To improve accuracy, researchers struggled to explore colour and motion features for flame detection. For instance, Chen et al[5]. studied the dynamic behavior and irregularity of flames in both RGB and HSI colour spaces for fire detection. Since their method considers the frame difference during prediction, hence, it fails to distinguish real fire from fire-like moving outliers and objects. Besides RGB and HSI color models, Marbach etal [9]. Explored the YUV colour model in combination with motion features for prediction of fire and non-fire pixels. A related method is proposed by Toreyin et al [6], by investigating temporal and spatial wavelet analysis, however, the extreme use of parameters by this method limits its effectiveness. Another method is presented by Han and Lee [10] by paralleling the video frames and their colour features for ame detection in tunnels.

Continuing the analysis of colour models, Celik and Demirel [11] used YCbCr with specific rules of splitting chrominance component from luminance. The method has the potential to notice ames with good accuracy but at a small distance and larger size of fire only. Considering these margins, Borges and Izquierdo [12] attempted to detect fire using a multimodal framework consisting of colour, skewness, and roughness features and Bayes classifier.

In extension with Borges and Izquierdo [12] work, multi-resolution 2D wavelets combined with energy and shape are explored by Rafiee et al [13]. in an attempt to decrease incorrect warnings, however, the false fire alarms still endured significant due to movement of rigid body objects in the scene. An promoted version of this approach is presented in [14] using YUC instead of RGB colour model, providing better results than [13]. Another colour based flame detection method with speed 20 frames/sec is suggested [15]. This scheme used SVM classifier to detect fire with good accuracy at a smaller distance. The method showed poor performance when a fire is at a larger distance or the amount of fire is comparatively small. Recapitulating the colour based methods, it is can be noted that such methods are delicate to brightness and shadows. As a result, the number of wrong warnings produced by these methods is very high. To deal with such issues, the ame's shape and rigid objects movement are investigated by Mueller et al [16]. The presented method uses optical flow information and behaviour of flame to intelligently extract a feature vector based on which flame and moving rigid objects can be segregated. Another related approach consisting of motion and color features is proposed by [17] for flame detection in surveillance videos. To further improve the accuracy, Foggia et al [14]. Combined shape, colour, and motion properties, resulting in a multi-expert framework for real-time flame detection. Although, the method dominated state-of-the-art flame detection algorithms, yet there is still space for development. In addition, the wrong alarming rate is still high and can be further reduced. From the above-mentioned literature, it is observed that fire detection accuracy has an inverse relationship to computational complexity.

III. SYSTEM DESIGN

The system design is the abstract model that defines the structure, behavior, and more views of the system. The system design is a formal report and demonstration of a system, structured in a way that supports reasoning about the structures and actions of the system.

3.1. System Architecture

A system architecture can consist of the system components and the sub-systems developed, that will work together to implement the whole system. There have been efforts to formalize languages to define system architecture; collectively these are called architecture description languages. The Figure 1 shows the system architecture of the fire detection system. In this Figure1 we show the process of training convolutional neural network model with training and testing, and also represents the process of producing the output.

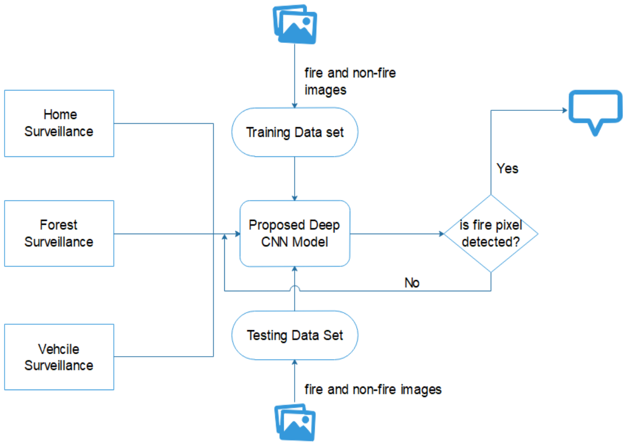

Figure 1. Fire Detection System Architecture.

The Figure 2 shows the system architecture of the accident detection system, represents the process of training TensorFlow object detection model with training data and also shows the construction of output data produced by TensorFlow Object detection technology.

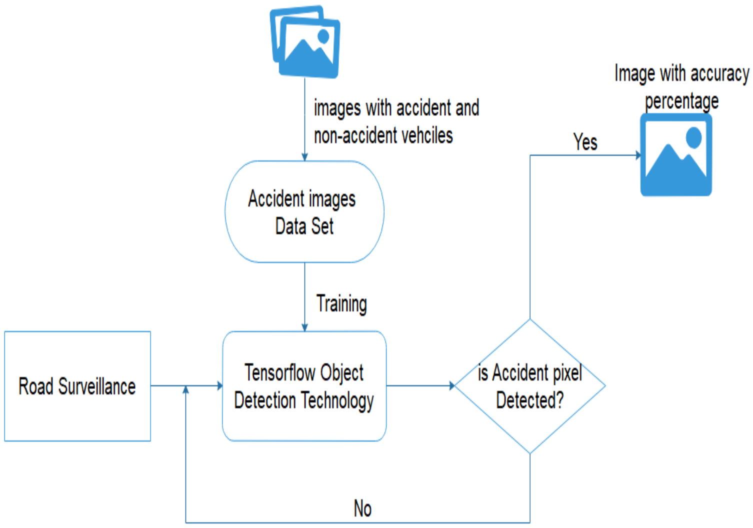

Figure 2. Accident Detection System Architecture.

3.2. Data Flow Diagrams

1. The DFD also called as bubble graph. It is an natural graphical formalism that can be worn to symbolize a scheme in terms of input data to the structure, a variety of dispensation allowed out on this record, and the output data is produced by this scheme.
2. The data flow diagram (DFD) is one of the mainly spirited modeling kits. It is used to model the system procedure, the data worn by the route, an outward unit that work together with the structure and the in-sequence flow in the system.
3. DFD shows how the sequence moves throughout the system and how it is customized by a series of transformation. It is a graphical method that portrays information stream and the transformation that are capable as data move from input to output.
4. A DFD may be used to symbolize a system at any level of abstraction. DFD may be partition into a level that represent rising in sequence stream and practical aspect.

The Figure 3 dataflow diagram of the fire detection system signifies the flow of data between different states involved in the fire detection system. The data flow diagram shows the procedure of transforming data from one state to another state.

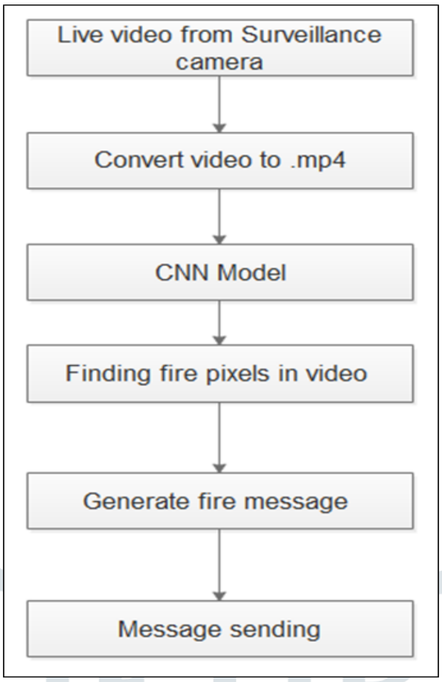

Figure 3. Fire Detection Data Flow Diagram.

The Figure 4 dataflow diagram of the accident detection system signifies the flow of data between different states involved in the fire detection system. The data flow diagram shows the process of transforming data from one state to another state.

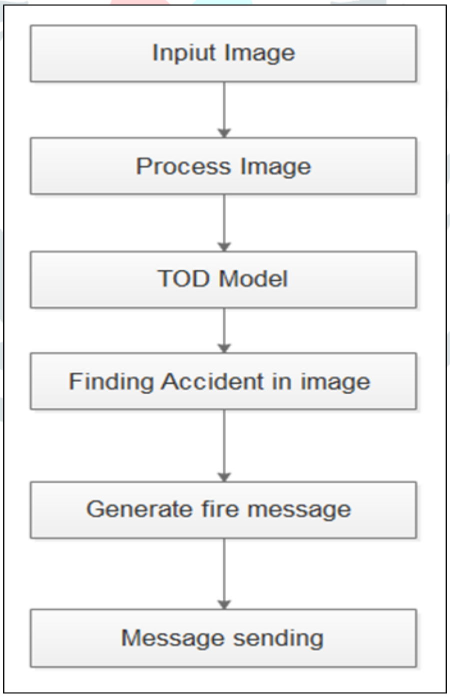

Figure 4. Accident Detection Data Flow Diagram.

IV. SYSTEM IMPLEMENTATION AND MODULES

A module is a software component or part of a program that comprises of one or more routines. One or more individually developed modules make up a program. An enterprise-level software application may contain several different modules, and each module serves distinctive and separate business operations.

Modules make a programmer's job easy by letting the programmer to focus on only one area of the functionality of the software application. Modules are typically merged into the program (software) through interfaces.

Software applications include many different tasks and procedures that cohesively serve all paradigms within a complete business solution. Initial software versions were gradually built from an original and simple level, and development teams did not yet have the ability to use prewritten-code.

The introduction of modularity permitted programmers to use again prewritten code with new applications. Modules were formed and bundled with compilers, in which each module performed a business or routine operation within the program. For example, Systems, Applications, and Products in Data Processing (SAP) an enterprise resource planning (ERP) software - includes several large modules (for example, finance, supply chain, and payroll, etc.), which may be carry out with little or no customization. A standard example of a module-based application is Microsoft Word, which comprises modules incorporated from Microsoft Paint that help operators create drawings or figures.

4.1. Convolutional Neural Network Module

In deep learning, a convolutional neural network (CNN) is a class of deep neural networks, most usually applied to analyzing visual imagery. CNN use a different multilayer perceptron's designed to require minimal preprocessing. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shade-weights architecture and translation invariance characteristics.

Convolutional networks were inspired by biological processes in that the connectivity pattern among neurons look like the union of the animal visual cortex. Individual cortical neurons react to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partly overlap such that they cover the whole visual field.

CNN use relatively slight pre-processing compared to other image classification algorithms. This means that the network studies the filters that in traditional algorithms were hand-engineered. This freedom from prior knowledge and human effort in feature design is a major benefit.

4.2. Convolutional Layers

Convolutional layers apply a convolution procedure to the input, passing the result to the following layer. The convolution competes with the response of an individual neuron to visual stimuli. Each convolutional neuron processes data only for its relevant field. Although fully connected feed forward neural networks can be used to study features as well as classify data, it is not practical to apply this architecture to images. A very high number of neurons architecture, due to the very large input sizes connected with images, where each pixel is a related variable. For instance, a fully connected layer for an image of size 100 x 100 has 10000 weights for each neuron in the second layer. The convolution operation conveys a solution to this problem as it diminishes the number of free parameters, allowing the network to be deeper with smaller quantity parameters. For instance, irrespective of image size, tiling regions of size 5 x 5, each with the same mutual weights, requires only 25 learnable factors. In this way, it resolves the vanishing or setting of gradients problem in training traditional multi-layer neural networks with many layers by using backpropagation.

4.3. Pooling

CNN may consist of local or global pooling layers, which syndicate the outputs of neuron clusters at one layer into a single neuron in the next layer. For example, max pooling uses the maximum value from each of a cluster of neurons at the preceding layer. Another example is average pooling, which uses the average value from each of a cluster of neurons at the preceding layer.

4.4. ReLU:

ReLU is an activation function. This layer eliminates early values in the filter image and replaces negative values with Zero's. This is done to avoid the value from summing up to Zero's.

Reactivation Linear Unit (RLU): Transform function only starts a node if the input is above a certain quality, while input is below zero. The output is zero, but when the input rises above a assured threshold, it has a linear relationship with the dependent variable, depicted in the Figure 5.

$$f(x) = \begin{cases} 0 \; if \; x < 0 \\ x \; if \; x \geq 0 \end{cases}$$

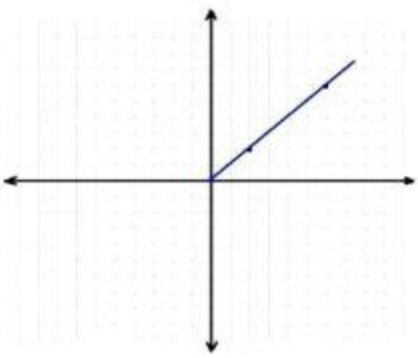

Figure 5. Linear Relationship Graph.

4.5. Fully connected

Fully connected layers connect every neuron in one layer to another layer. It is in principle the same as the traditional multi-layer perceptron neural network (MLP). The attened matrix goes through a fully connected layer to categorize the 1 images. The Figure 6 Convolutional Neural Network model used in the fire detection system contains the architecture of CNN model. This CNN model diagram indicates the construction of the CNN model with Conv layers, Pooling layers, and ReLU activation functions to build more accurate image classification neural network.

V. RESULTS AND DISCUSSIONS

Results contain all data about input and output formats of our project. Results specify that what the way input is taken by the application and specify the format of final output attained from our fire and accident detection system.

The Figure 7 shows the picture which indicates the accident of a car. As it is recognized as an accident, this will be taken as an input. Through this input, the resultant output will be generated by showing an accurate accident result.

In Figure 8, the resultant output figure which is generated through the given input. The figure shows the accuracy level of the car accident which is represented in the rectangular block.

The Figure 9 shows the pixel representation of the output image which is implemented through the input. This represents the image which includes the fire pixels and this image is divided based on the intensity of the fire. If the fire is identified in the pixels, those are represented in green color otherwise red color. This makes us identify the fire precision in the image.

5.1. Comparison of Existing and Proposed Systems

The Table 1 represents the differences and Comparisons between existing system and proposed system of fire and accident detection systems based on some parameters which are used in implementation of fire and accident detection system.

One of the crucial advantages of the proposed system is that our server can process the data of 16 surveillance cameras.

Installation of Existing system of fire and accident detection requires more human power because the existing system contains hardware devices to detect fire and smoke. Proposed system contains software files to detect fire and accidents, so installation is done in a short span of time with not as much of human power.

Existing system uses traditional 2 methods of fire and accident detection. It takes nearly 1 to 3 minutes of time to detect fire and accident. The proposed system uses advanced technologies of Neural Network which takes less time to compare to the existing system. The proposed system is executed within 40 to 50 seconds (30 seconds for video capturing and 10 to 15 seconds for execution of Neural Network) to detect fire and accidents.

Components used in the existing system is sensors and smoke detection hardware components. It takes more time to detect fire and accidents compared with the newest technologies. The proposed system is implemented with TensorFlow GPU technology which is technologically advanced by Google for easy processing of 3D objects. TensorFlow is the latest technology with high processing speed. By using this technology proposed system is detected fire and accident components in an early stage.

Technologies used in existing system are Internet of Things and Image Processing. These technologies have a lesser amount of processing speed. The proposed system is implemented with TensorFlow Technology and TensorFlow Object Detection Technology in Neural Network. These technologies are executed much faster than existing system to notice fire and accidents.

Every system implementation is mainly concentrated on accuracy level of final output obtained from the system. Existing systems of fire and accident detection get outputs with 90-92 percentage of accuracy. The proposed system is getting outputs with 95-98 percentage of accuracy.

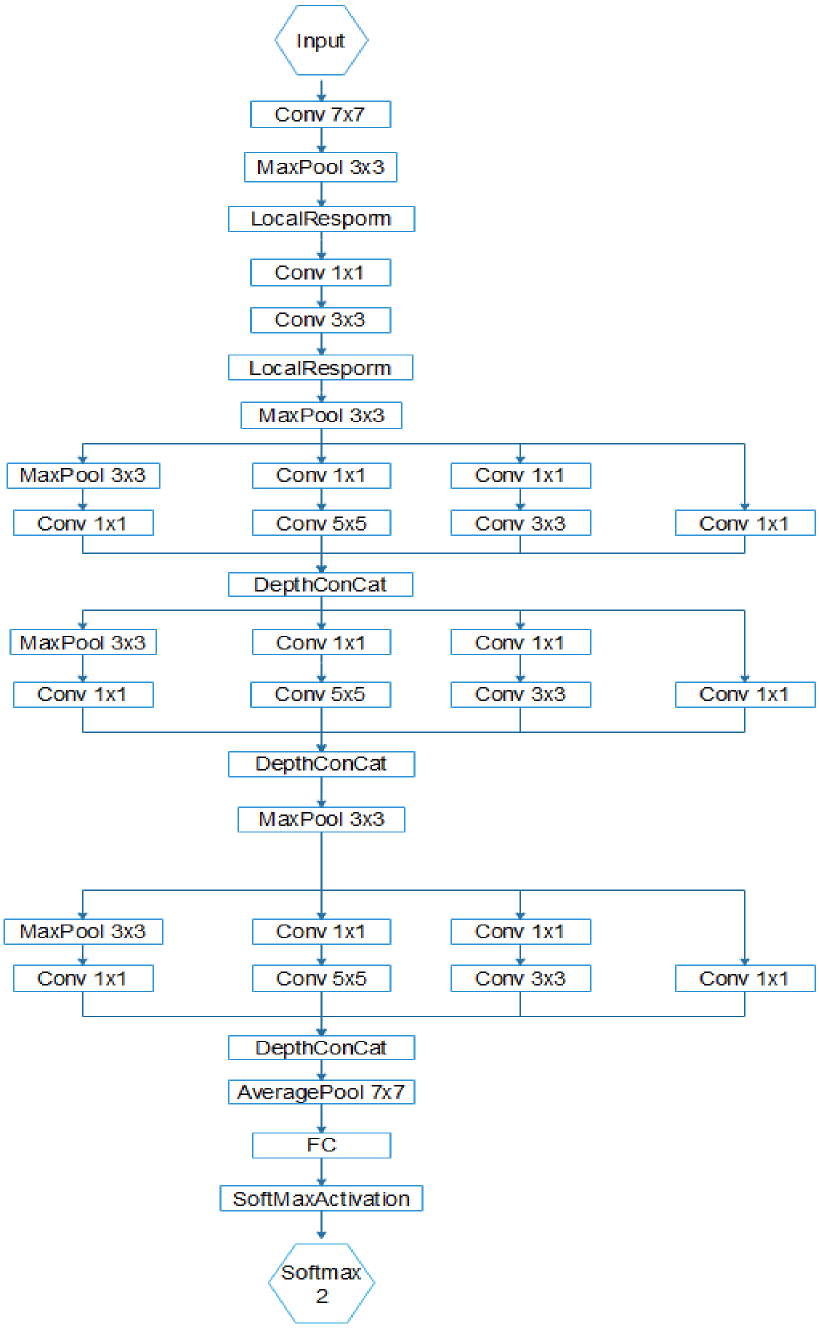

Figure 6. CNN Model Architecture.

Figure 7. Accident input image.

Figure 8. Incident accuracy level.

Figure 9. Super pixel implementation example.

Table 1. Comparison between Existing System and Proposed System.

Parameter	Existing System	Proposed System
Installation of fire and smoke detection system	Requires more human power to install all hard ware components.	Easy to install because of software files.
Time to detect fire and smoke	1 to 3 minutes	40 seconds (30 seconds for video capturing+10 seconds for execution of neural network)
Components used in fire and smoke detection system	Existing system contains sensors to detect fire and accidents.	Proposed system uses TensorFlow GPU technology of Neural Network.
Technologies used in fire and accident detection system	Internet of Things, and Image processing.	Advanced methods and Technologies of Neural Network is used in fire and accident detection system.
Accuracy	90 to 92 % accuracy	95 to 98% accuracy

VI. CONCLUSIONS AND FUTURE SCOPE

When everyday social situations and cultural phenomena come to be associated with a threat to security, security becomes a value which strives with other values particularly the right to privacy and human rights. Security appears as an apparent choice over the loss of some aspects of other values and is seen as a reasonable and worthwhile sacrifice because of what security promises to deliver. A number of organizations and working group are putting their efforts to strengthen security. Working groups are releasing their drafts and report on critical security threats and recommending various methods to counter them. This is especially noticed for videos. Experimental, analytical and visual tests conducted over a set of benchmark videos reveals a competitive performance of our proposed algorithm as compared to that of the state-of-the-art algorithms.

Fire and accident detection system is extended by maintaining a centralized server contain fire and accident detection software. Group of surveillance cameras is connected with this server and videos captured by the surveillance camera are processed with high configured computational devices maintained to get results more accurately at less time associated with the traditional methods. Maintaining servers reduces the cost of implementation and manageable for every individual at a low cost.

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