FIRE AND SMOKE DETECTION USING DEEP LEARNING

A PROJECT REPORT

for

Soft Computing

in

B.Tech (IT)

by

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Under the Guidance of
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SITE

Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)

School of Information Technology and Engineering

JUNE,2022

DECLARATION BY THE CANDIDATE

We here by declare that the project report entitled **“FIRE AND SMOKE DETECTION USING DEEP LEARNING”** submitted by us to Vellore Institute of Technology University, Vellore in partial fulfillment of the requirement for the award of the course **“Soft Computing and id”** is a record of bonafide project work carried out by us under the guidance of **HEMALATHA S** We further declare that the work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other course.

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Signature

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CERTIFICATE

This is to certify that the project report entitled **"FIRE AND SMOKE DETECTION USING DEEP LEARNING"** submitted by **Manish Rao (19BIT0333), CHAVAN MUKUL MANISH (20BIT0238), VIKRANT KUMAR YADAV (20BIT0149)** to Vellore Institute of Technology University, Vellore in partial fulfillment of the requirement for the award of the course **Soft Computing** is a record of bonafide work carried out by them under my guidance.

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FIRE AND SMOKE DETECTION USING DEEP LEARNING

Sample: A Hybrid Intelligent System Framework for the Prediction of fire and smoke using deep learning Algorithms

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Abstract

The technologies underlying fire and smoke detection systems play a crucial role in ensuring and delivering optimal performance in modern surveillance environments. For this majority of cities have already installed camera-monitoring systems, this encouraged us to take advantage of the availability of these systems to develop cost-effective vision detection methods. However, this is a complex vision detection task from the perspective of deformations, unusual camera angles and viewpoints, and seasonal changes. To overcome these limitations, we want to propose a new method based on a deep learning approach, which uses a convolutional neural network that employs dilated convolutions. An evaluation on the method be collected from the internet and labeled manually. The experimental results are expounded be done by

training and testing it on custom-built dataset, which consists of images of fire and smoke that would act to indicate the classification performance and complexity of the method are superior. In addition, the method would be designed to be well generalized for unseen data, which offers effective generalization and reduces the number of false alarms.

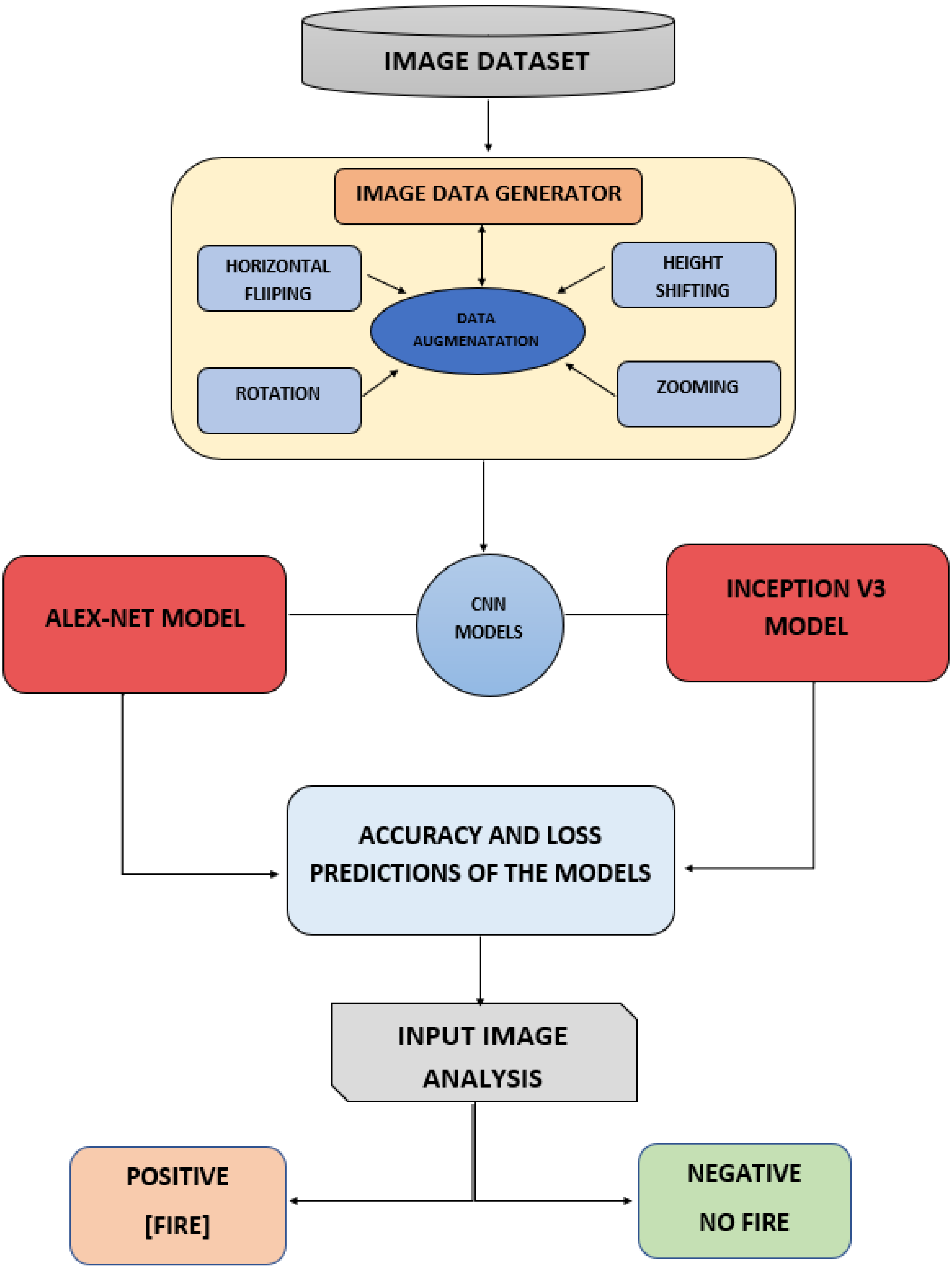
I. INTRODUCTION

A fire is a chemical reaction in which a carbon-based material (fuel), mixes with oxygen (usually as a component of air), and is heated to a point where flammable vapors are produced. These vapors can then come in contact with something that is hot enough to cause vapor ignition, and a resulting fire. In simple terms, something that can burn touches something that is hot, and a fire is produced. [1]. When the ignition source contacts the fuel, a fire can start. Following this contact, the typical accidental fire begins as a slow growth, smoldering process which may last from a few minutes to several hours. The duration of this "incipient" period is dependent on a variety of factors including fuel type, its physical arrangement, and quantity of available oxygen.[2] During this period heat generation increases, producing light to moderate volumes of smoke. The characteristic smell of smoke is usually the first indication that an incipient fire is underway. It is during this stage that early detection (either human or automatic), followed by a timely response by qualified fire emergency professionals, can control the fire before significant losses occur. [3]. To minimize fire risk and its impact, we should develop and implement comprehensive and objective fire protection programs. Program elements should include fire prevention efforts, build, methods to detect developing fire and alert emergency personnel, and means to effectively extinguish a fire. [4]. The role of fire detection systems is to have a key aspect of fire protection is to identify a developing fire emergency in a timely manner, and to alert the occupants and fire emergency organizations. [5]. The basic aspects of the fire detection systems can be included as the control panels, fire detectors, alarm output devices, fire sprinklers and many others. [6]. The control panel is the "brain" of the fire detection and alarm system. It is responsible for monitoring the various alarm input devices such as manual and automatic detection components, and then activating alarm output devices such as horns, bells, warning lights, emergency telephone dialers, and building controls.[7]. Smoke detectors are a much newer technology, having gained wide usage since previous three-four decades in residential and life safety applications. As the name implies, these devices are designed to identify a fire while in its smoldering or early flame stages, replicating the human sense of smell.[8]. Upon receiving an alarm notification, the fire alarm control panel must now tell someone that an emergency is underway. This is the primary function of the alarm output aspect of a system. Occupant signaling components include various audible and visual alerting components, and are the primary alarm output devices.[9]. Moreover, excluding the above mentioned, a new methodology like capturing the fire smoke and related pictures and analyzing them and predicting gives a new inventory ide to the science and its humans. [10] There is a look into the study because capturing gives both the fog and smoke images which rises to the confusion and various artificial algorithms must be studied which could overcome it. [11] Deep Learning, CNN techniques with various sub steps can make it more understandable and a valuable study over it with comparisons can give a good extract of results. [12] Success is dependent upon selection of proper suppression and detection components and a good algorithm comparisons study result [13].

II. BACKGROUND

Object Detection has been witnessing a rapid revolutionary change in the field of computer vision. Its involvement in the combination of object classification as well as object localization makes it one of the most challenging topics in the domain of computer vision. In simple words, the goal of this detection technique is to determine where objects are located in a given image called as object localization and which category each object belongs to, that is called as object classification. According to the principle of object detection algorithms, the flow of image fire detection algorithms is based on convolutional neural networks. The detection CNN has functions of region proposals, feature extraction and classification. Firstly, The CNN takes an image as input and outputs region proposals by convolution, pooling. A convolutional neural network (CNN) is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data. Pooling function is to progressively reduce the spatial size of the representation to reduce the number of parameters and computation in the network which operates on each feature map independently Secondly, the region-based object detection CNN decides the presence or absence of fire in proposal regions through convolutional layers, pooling layers, fully-connected layers, etc. Inspired by the great potential of CNNs, object detection algorithms we can detect fire from images or videos at an early stage is the motto behind the study.

ARCHITECTURE DIAGRAM



III. LITERATURE SURVEY:

[1]. This paper proposes a method to detect fire using deep learning. Deep learning networks used in the proposal were AlexNet, GoogLeNet and VGG-16 in three ways. Image input from a closed circuit television (CCTV) camera is classified into three different states (normal, smoke and flame) and then the network is trained to recognize each corresponding state. AlexNet showed more than 94.00% accuracy, GoogLeNet had more than 95.00% accuracy, and VGG-16 had more than 96.00% accuracy. Images that are erroneously identified commonly contained features similar were classified images such as fire, non-fire, smoke, neutral and so on.

[2]. The paper deals with the detection of fire by analysing videos acquired by surveillance cameras. Traditional sensor-based fire detection systems cannot be alerted until the heat actually reach to the sensors. Therefore, it is evident to make a fast, robust and reliable system which can detect fire at an early stage. We propose a method that is able to detect fire by analysing videos acquired by surveillance cameras. Recent development in Deep Learning has been proved to be highly effective in the field of computer vision. Transfer Learning (a deep learning methodology) has emerged to be extremely helpful for the applications with scarcity of training data and a deep content of dataset have been analysed to deal with the study here.

[3]. The purpose of this paper is to present a new smoke detection method by using surveillance cameras. The proposed method is composed of two stages. In the first stage, motion regions between consecutive frames are located by using optical flow. In the second stage, a deep convolutional neural network is used to detect smoke in motion regions. Early fire detection in indoor environment is essential for people’s safety. During the past few years, many approaches using image processing and computer vision techniques were proposed. However, it is still a challenging task for the application of video smoke detection in an indoor environment, because of the limitations of data for training and lack of efficient algorithms. Thus, the above-mentioned algorithms are used to overcome the past study and bring a new bootstrap to the fire detection field.

[4]. Early detection of wildfires is a critical modern-day challenge for first responders and emergency services. The existing systems for wildfire detection include video surveillance with high-end cameras using pattern recognition and satellite-based monitoring, which gives a high-cost rate. These systems are very expensive which makes them beyond the reach of medium to small scale users. In prior work, it dealt with the proposal of a low-power and low-cost wildfire monitoring system based on distributed sensor networks. Convolutional Neural Networks (CNNs) have been instrumental in improving the accuracy of image classification. The model is based on

SqueezeNet and has a very small storage footprint; Computationally, the proposed model is much more efficient as well which is based on feature map selection

[5]. The paper deals with the content of fire detection based on the determination of people, object, event or condition from the images is performed using deep learning structures in environments monitored by cameras. One of the situations can be considered as the determination of fire and its marker smoke. One of the problems in detection of smoke is the foggy environment. In this work, the detection of smoke for foggy environments using deep learning models is performed. Images obtained from various video databases containing smoke and non-smoke samples are augmented by adding artificial fog.

[6]. Fire disasters are man-made disasters, which cause ecological, social, and economic damage. To minimize these losses, early detection of fire and an autonomous response are important and helpful to disaster management systems. To achieve this goal, the study explored deep CNNs and devised a fine-tuned architecture for early fire detection during surveillance for effective disaster management systems. After successful fire detection, another desirable requirement is to send an immediate alert to the disaster management system along with the representative keyframes. In end it has been discussed about Dynamic channel selection using cognitive radio networks to bring a charm to the study.

[7]. The paper is all about the research on fire detection using wireless sensor network and video-based methods is a very hot research topic. In this paper, the study proposed a fire detection method which is based on powerful machine learning and deep learning algorithms. The previously existing method WSN have been considered for study reference. Both sensors' data as well as images data for fire prevention are used. The proposed model has three main deep neural networks i.e., a hybrid model which consists of Adaboost and many MLP neural networks, Adaboost-LBP model and finally convolutional neural network.

[8]. Video smoke detection (VSD) is a prospective and effective solution for fire detection in spacious buildings and forests. Most of the deep learning based VSD model are end-to-end models, and the intrinsically knowledge of the smoke, such as the motion and colour which are obvious and effective for detection have not been utilized effectively. In order to improve the detection rate and reduce the false positive rate of the VSD systems, domain knowledge of smoke was used to segment suspected smoke regions in a video frame firstly in this detection framework using the CNN and the Gaussian Mixture Model.

[9]. With recent advances in embedded processing capability, vision-based real-time fire detection has been enabled in surveillance devices. This paper presents an image-based fire detection framework based on deep learning. The key is to learn a fire detector relying on tiny-YOLO (You Only Look Once) v3 deep model. With the advantage of lightweight architecture of tiny-YOLOv3 and training data augmentation by some parameter adjusting, our fire detection model can achieve better detection accuracy in real-time with lower complexity in the training stage. Experimental results have verified the effectiveness of the proposed framework.

[10]. Fire is one of the most commonly occurring disasters and is the main cause of catastrophic personal injury and devastating property damage. An early detection system is necessary to prevent fires from spreading out of control. In this paper, we propose a multistage fire detection method using convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. In the first stage, fire candidates are detected by using their salient features, such as their colour, flickering frequency, and brightness. In the second stage, a pretrained CNN model is used to extract the 2D features of flames that are the input for the LSTM network.

[11]. Wildfires are one of the costliest and deadliest natural disasters in the US, causing damage to millions of hectares of forest resources and threatening the lives of people and animals. Of particular importance are risks to firefighters and operational forces, which highlights the need for leveraging technology to minimize danger to people and property. FLAME (Fire Luminosity Airborne-based Machine learning Evaluation) offers a dataset of aerial images of fires along with methods for fire detection and segmentation which can help firefighters and researchers to develop optimal fire management strategies. A deep learning method is designed based on the U-Net up-sampling and down-sampling approach to extract a fire mask from the video frames. The method approached a precision of 92%, and recall of 84%.

[12]. The automation of fire detection systems can reduce the loss of life and property by allowing a fast and accurate response to fire accidents. Although visual techniques have some advantages over sensor-based methods, conventional image processing-based methods frequently cause false alarms. Recent studies on convolutional neural networks have overcome these limitations and exhibited an outstanding performance in fire detection tasks. Nevertheless, previous studies have only used single-scale feature maps for fire image classification, which are insufficiently robust to fires of various sizes in the images.

[13]. Hand-designed features are used to reduce computation load and false alarm rate. A study proposed a small and efficient CNN model for fast and intelligent smoke detection. The method has excellent performance and generalization ability in new environments. The detection time of a single frame was detected by 36.45 ms with a CPU and multithreading. A SqueezeNet model has been proposed to the work. Various iteration steps for same model have been performed to evaluate the study.

[14]. Flame detection is an increasingly important issue in intelligent surveillance. In fire flame detection, we need to extract visual features from video frames for training and test. Based on them, a group of shallow learning models have been developed to detect flames, such as color-based model, fuzzy-based model, motion and shape-based model, etc. Deep learning is a novel method which could be much efficient and accurate in flame detection. In this paper, we use YOLO model to implement flame detection and compare it with those shallow learning methods so as to determine the most efficient one for flame detection.

[15]. Forest fires are one of the most destructive and frequent natural disasters that destroy forest areas and cause the deaths of thousands of people and millions of animals around the world. Often the fight against forest fires is complicated by the untimely receipt of information about the disaster that has occurred, it requires more effort than if the fire had been known from the very beginning of the fire. This paper describes a prototype system for determining areas of fire in the image from a quadcopter using neural network technology. CNN, neural network has been discussed and majorly highlighted with the Inception V3 model in the paper.

[16]. This paper proposes a novel method for fire and smoke detection using video images. The ViBe method is used to extract a background from the whole video and to update the exact motion areas using frame-by-frame differences. Dynamic and static features extraction are combined to recognize the fire and smoke areas. For static features, we use deep learning to detect most of fire and smoke areas based on a Caffemodel. Another static feature is the degree of irregularity of fire and smoke. An adaptive weighted direction algorithm is further introduced to this paper. To further reduce the false alarm rate and locate the original fire position, every frame image of video is divided into 16×16 grids and the times of smoke and fire occurrences of each part is recorded.

[17]. For the purpose of accidental fires and natural fire, several attempts have been made to detect fire in advance. In order to detect fire detection through an image rather than a sensor area, large amounts of data are required to learn detection model. However, in special cases such as fire, the collection of these data is limited. In this paper, we propose a method to learn the detection model by using this limited data as self-generated or synthesized learning data. The synthesized

[18]. This paper combines forest fire identification with deep learning algorithm in the field of machine learning, utilizes a convolutional network module specifically designed for dense prediction of flame subregion. The presented module uses dilated convolutions to systematically aggregate multi-scale contextual information without losing resolution. The architecture is based on the fact that dilated convolutions support exponential expansion of the receptive field without loss of resolution or coverage.

[19]. Research on video analysis for fire detection has become a hot topic in computer vision. However, the conventional algorithms use exclusively rule-based models and features vector to classify whether a frame is fire or not. These features are difficult to define and depend largely on the kind of fire observed. The outcome leads to low detection rate and high false-alarm rate. A different approach for this problem is to use a learning algorithm to extract the useful features instead of using an expert to build them. In this paper, we propose a convolutional neural network (CNN) for identifying fire in videos. Convolutional neural network is shown to perform very well in the area of object classification. This network has the ability to perform feature extraction and classification within the same architecture. Tested on real video sequences, the proposed approach achieves better classification performance as some of relevant conventional video fire detection methods and indicates that using CNN to detect fire in videos is very promising.

[20]. There has been an array of methods proposed using Deep Learning, Convolutional Neural Networks (CNNs) to automatically detect and predict flame and smoke in videos and images. In this paper, we present a complete survey and analysis of these machine vision-based fire/smoke detection methods and their performance. Firstly, we introduce the fundamentals of image processing methods, CNNs and their application prospect in video smoke and fire detection. Next, the existing datasets and summary of the recent methodologies used in this field are discussed. Finally, the challenges and suggested improvements to further the development of the application of CNNs in this field are discussed. CNNs are shown to have a great potential for smoke and fire detection and better development can help prepare a robust system that would greatly save human lives and monetary wealth from getting destroyed from fires.

Name of algorithm/technique	Advantages of techniques	Disadvantages of using this technique
Deep Neural Network	• The neural network-based approach can be applied to many different applications and data types • Deep learning architecture is flexible to be adapted to new problems in future • Features are automatically deduced and optimally tuned for desired outc ome	• The technique needs large amount of data in order to perform better than the other techniques • It’s extremely expensive to train fur to complex data models
Alexnet	• AlexNet was the first major CNN model that used GPUs for training. This led to faster training of models. • AlexNet is a deeper architecture with 8 layers which means that is better able to extract features when compared to LeNet. It also worked well for the time with color images. • The ReLu activation function used in this network has 2 advantages. It does not limit the output unlike other activation functions. This means there isn’t too much loss of features. • It negates the negative output of summation of gradients and not the dataset itself. This means that it will further improve model training speed since not all perceptron are active.	• The depth of this model is very less and compare to others, hence it struggles to learn features from image sets. • It is observed that it takes more time to achieve higher accuracy results compared to future models.
Inception V3	• It has higher efficiency • It has a deeper network compared to the Inception V1 and V2 models, but its speed isn't compromised.	• The model has fewer parameters and lower computational complexity than other methods.

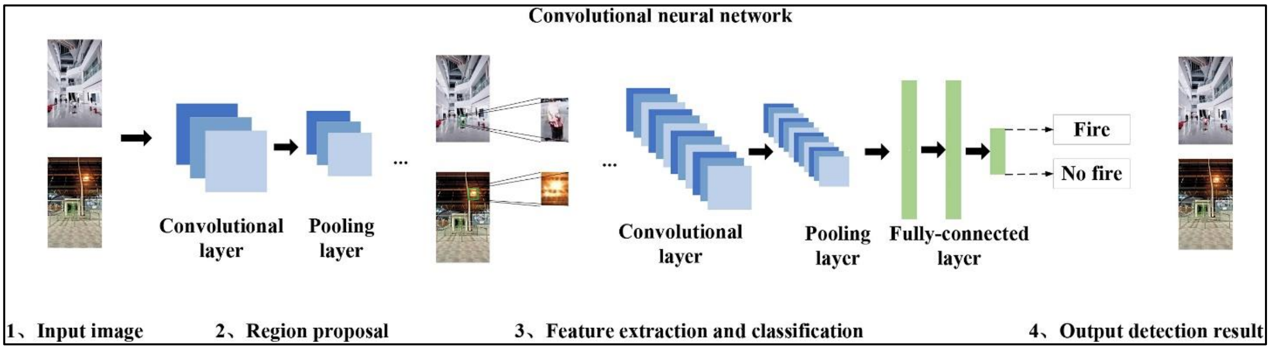
	• It is computationally less expensive. • It uses auxiliary Classifiers as regularizes. • The model reduces the parameter space by decomposing spatial convolutions with larger filter sizes (n×n) into a sequence of two convolutional operations with respective filter sizes of n × 1 and 1 × n.	• Unlike other models considered in this work, no fully-connected layers are used in here.
ResNet	• The ResNet architecture does not need to fire all neurons in every epoch. This greatly reduces the training time and improves accuracy. Once a feature is learnt, it does not try to learn it again but rather focuses on learning newer features. A very smart approach that greatly improved model training performance. • The complexity of an identical VGG network caused the degradation problem which was solved by residual learning.	• We see a drastic improvement in achieving high accuracy and low loss. The concept of residual learning can be called a major breakthrough in Neural Networks. • The model created from the ResNet architecture also had a low validation loss which meant that there was no over-fitting happening while training
VGG	• VGG brought with it a massive improvement in accuracy and an improvement in speed as well. This was primarily because of improving the depth of the model and also introducing pretrained models. • The increase in the number of layers with smaller kernels saw an increase in non-linearity which is always a positive in deep learning. • VGG brought with it various architectures built on the similar concept. This gives more options to us	• One major disadvantage that I found was that these model experiences the vanishing gradient problem. If we look at my validation loss graph, we clearly see it increasing as a trend. This wasn't the case with any of the other models. The vanishing gradient problem was solved with the ResNet architecture. • VGG is slower than the newer ResNet architecture that

	as to which architecture could best fit our application.	introduced the concept of residual learning which was another major breakthrough.

Table suggesting the diverse applications in watermarking scheme available offered by various techniques.

IV. PROPOSED ALGORITHM

Convolutional neural network (CNN), a class of artificial neural networks that has become dominant in various computer vision tasks, is attracting interest across a variety of domains, including radiology. CNN is designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks, such as convolution layers, pooling layers, and fully connected layers. Understanding the CNN working by a sequence of steps shown in image gives a good clarity.



The customized CNN models work with the generation of image to the data format using data augmentation techniques. Data augmentation is a technique of altering the existing data to create some more data for the model training process. It is the process of artificially expanding the available dataset for training a deep learning model.

Augmentation techniques: horizontal flipping, rotation and height shifting techniques are applied to the dataset for its own benefits like improving performance and outcomes of the respective model

The proposed algorithm works on two different models but on the same algorithm technique. The two custom CNN models have been implemented for a cost-effective fire detection CNN architecture for surveillance videos. The first model is a customized basic CNN architecture inspired by AlexNet architecture and the other deals by creating a customized InceptionV3 model.

CUSTOMIZED ALEXNET CNN MODEL

AlexNet was the first convolutional network consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer. Each convolutional layer consists of convolutional filters and a nonlinear activation function ReLU. The pooling layers are used to perform max pooling. Input size is fixed due to the presence of fully connected layers. The input size is mentioned at most of the places as 224x224x3 but due to some padding which happens it works out to be 227x227x3. AlexNet overall has 60 million parameters

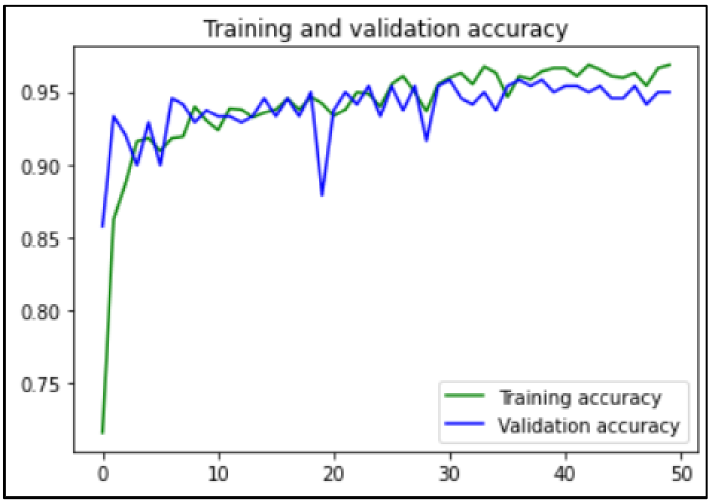
CUSTOMIZED INCEPTION V3 MODEL

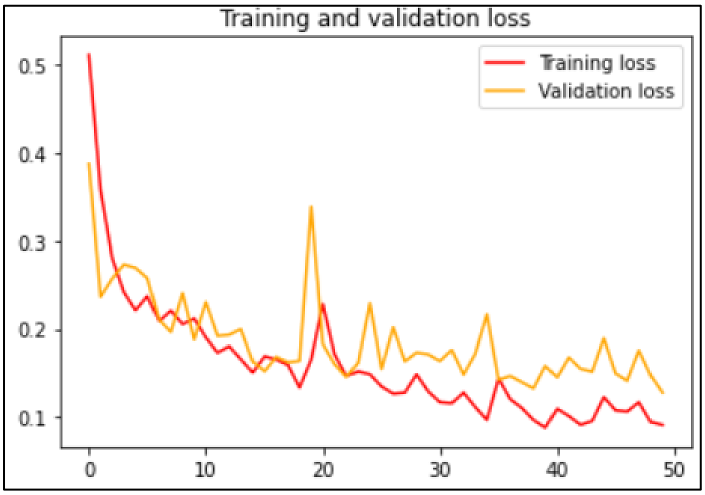
Inception-v3 is a convolutional neural network that is 48 layers deep. It can load a pretrained version of the network trained on more than a million images from a dataset. The pretrained network can classify images into 1000 object categories, such as fire, no fire in our case. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299. In an Inception v3 model, several techniques for optimizing the network are suggested to loosen the constraints for easier model adaptation. The techniques include factorized convolutions, regularization, dimension reduction, and parallelized computations.

V. EXPERIMENTS RESULTS

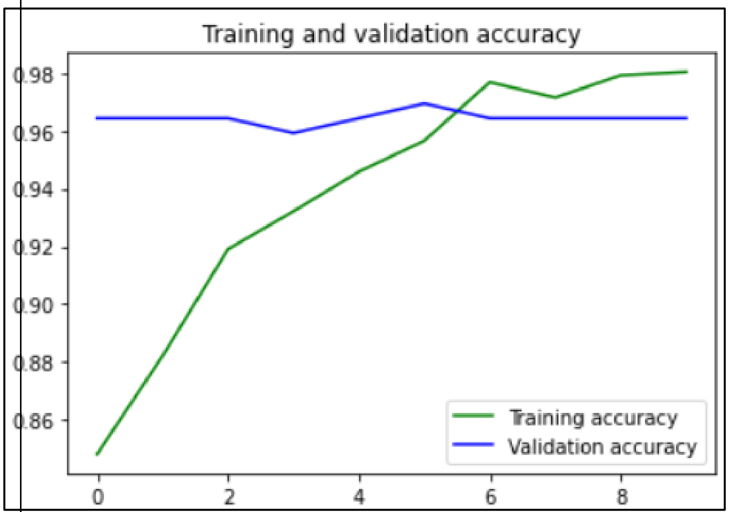
In this section of the project involved the discussion on the classification models and outcomes from different perspectives. First, we checked the performance of different machine learning algorithms such as logistic regression, k-nearest Neighbor, artificial neural network, support vector machine, Naive Bayes, and decision tree on Cleveland heart disease dataset on full features. In the second, we used feature selection algorithm Relief, mRMR, and LASSO for important features selection. In third classifiers, performances were checked on selected features. Also, the k-fold cross-validation method was used.

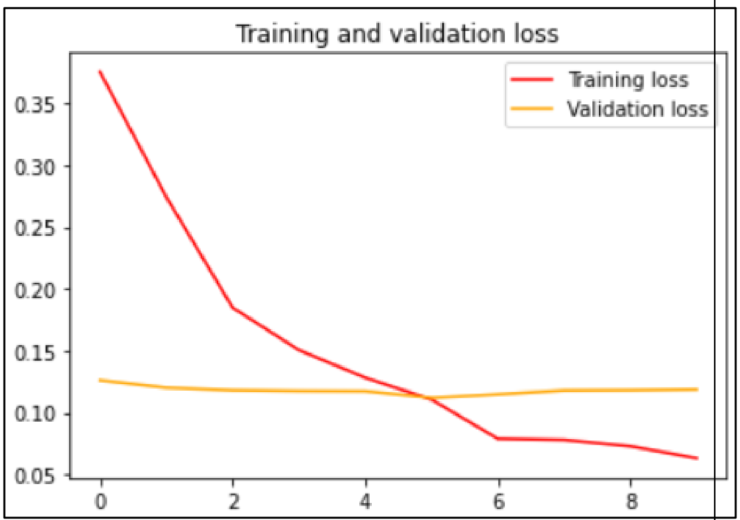
The results of PSNR from attacked image and original image drives the fact that our scheme is robust to distortion on applications of digital image processing attacks and geometrical attacks.





AlexNet Model





Inception V3 Model

VI. COMPARATIVE STUDY

Since we have been going via various architecture methods like the Inception V3 model and AlexNet model, we majorly compare the training accuracy, validation accuracy, training losses and validation losses. We train the model using the training data and check its performance on both the training and validation sets. The training loss indicates how well the model is fitting the training data, while the validation loss indicates how well the model fits new data.

Type	Value
Training accuracy	98.04
Validation accuracy	96.43
Training loss	0.063
Validation loss	0.118

Inception V3 Model

Type	Value
Training accuracy	96.83
Validation accuracy	94.98
Training loss	0.09
Validation loss	0.13

AlexNet Model

VII. CONCLUSION AND FUTURE WORK

In this embedded project work, we understood that by using smart cameras we can identify various suspicious incidents such as collisions, medical emergencies, and fires. Of such, fire is the most dangerous abnormal occurrence, because failure to control it at an early stage can lead to huge disasters, leading to human, ecological and economic losses. Inspired by the great potential of CNNs, we can detect fire from images or videos at an early stage. It dealt with two custom models for fire detection. Considering the fair fire detection accuracy of the CNN model, it can be of assistance to disaster management teams in managing fire disasters on time, thus preventing huge losses We analyzed that training and validation accuracy of Inception V3 model was better than the AlexNet on and so the losses were also less.

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