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Forest Fire Detection Using Satellite Imagery

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***Abstract*- In this paper, we propose an inventive system for detecting fire using You Only Look Once (YOLO) and Computer Vision (OpenCV). Detecting a fire using present and conventional techniques of smoke sensors installed can be extremely difficult. Because of their primitive design and technology, they are slow and inefficient. This paper examines the scope of Computer Vision and Object Detection for detection and alerting with video from sources such as images videos from live feed or CCTV. This project makes use of a self-created dataset containing video frames with fire. The data is then preprocessed before being used to build a machine learning model with YOLO. The dataset's test set is provided as input for validating the algorithm, and experiments are recorded. The project's goal is to create a low-cost, high-accuracy machine that can be used in almost any real-time fire detection application.**

Keywords: Fire detection, YOLO, Machine learning, CCTV, Computer Vision , OpenCV,Object detection.

I. INTRODUCTION

In today's hectic world fire can be a serious threat. Due to fire, all buildings and vehicles used for public transportation have fire protection and fire protection. Furthermore, many businesses hold fire drills every few months to protect their employees from fire. This will assist them in understanding what they should and should not do in the event of a fire. Forests play an important role in maintaining ecological balance. When forest fires occur, this becomes extremely problematic. It is more common, however, when fires spread over a large area. Fire cannot always be put out. As a result, the environmental damage has been greater than anticipated. The environment is harmed by large amounts of carbon dioxide (CO_2) released by forest fires. It will also lead to the extinction of rare species around the world (Alkhatib, 2014). Weather conditions can also have an impact on it, causing serious problems such as earthquakes, heavy rains, and floods.

The forest is a sizeable region covered in trees, tonnes of , dried leaves, timber and other things. When the fire first ignites, these substances help it grow. Numerous factors, including smoking, high summer temperatures, and fireworks-filled gatherings, might start a fire. Once a fire starts, it won't stop until it has entirely burned itself out. If the fire is discovered as soon as possible, the damage and the expense for distinguishing the fire can be decreased. Therefore, in this situation, fire detection is crucial. Finding the exact spot of the fire and alerting the fire officials quickly after the fire occurs can have a good effect.The government uses a variety of fire detection techniques, including optical cameras, sensors, tower monitoring, satellite monitoring, and more.

There are many other methods used for fire suppression. The main one is setting fire to dry lands, or, as in Canada, utilizing flying water tanks to put out fires. These elements sweep it away in middle eastern nations, where it is then burned in a specific area without fuel. However, in Australia, they set fire to these regions and wait for it to go out on its own without endangering either the wildlife or people.

A research study demonstrates that there are three categories of automated fire detection: aerial, ground, and borne detection. The ground-based devices use a number of stationary black-and-white video cameras to identify smoke from fires and compare it to ambient smoke. High spatial and temporal resolution is the key advantage of this system. The detection will be simpler as a result (Eric den Breejen, 1998). However, there are still some issues with these methods in terms of spotting a fire in its early stages. Therefore, it is crucial to implement a system to identify fires as soon as possible.

II. EXISTING SYSTEM

III. The current fire detection systems rely on traditional responses like smoke and heat alarms. A single module is not adequate to monitor all of the potential hot spots for fires, which is the fundamental drawback of smoke sensor alarms and heat sensor alarms. The only way to avoid a fire is to exercise constant caution. Even if they are set up in every crevice, it simply is not enough to constantly produce an effective output, and it is almost impossible to install fire detectors in every region of a forest that is prone to fire. The price will rise by a multiple as the number of smoke detectors required rises.

IV.

V. Within minutes of an accident or fire, the suggested method can generate reliable and extremely accurate alerts. One piece of software powers the entire surveillance network, which lowers costs. Data scientists and machine learning experts are actively conducting research in this area. The key problem is reducing inaccuracy in fire detection and timely alert and incident report transmission.

VI. LITERATURE REVIEW

The author employs CNN-convolutional neural networks to detect fire using live video material obtained from anti-fire surveillance equipment. According to the paper [1,] the YOLOv2 convolutional neural network is one of the best methods for detecting fire and smoke both indoors and outdoors. You only look once (YOLO) is a deep learning model for object detection; YOLOv2 is the upgraded version that addresses YOLO's shortcomings, namely the inability to accurately locate and mark the region of interest in images and the lower recall rate when compared to other region-oriented algorithms. As a result, the architecture's efficiency improves. They started with a 128x128x3 input picture. Convolutional layers were utilised to map the characteristics on the input image.The features extracted are then given as input to YOLOv2 object detection subnetwork. YOLOv2 Transform layer is implemented to improve network stability for object localization.

In his work, Qingjie Zhang proposes that vision-based fire detection devices that may be attached to an unmanned aerial vehicle (UAV) for strategically monitoring acreage of fire prone areas can detect forest fires. Paper [2] also strongly suggests Convolutional neural networks for detecting smoke and fire using videoframes as pictures. They gathered the data from several internet sites. They scaled the photos to the standard size of 240x320. The primary idea behind this research is to find the fire patches in an image. The authors provide two ways for the algorithm to construct the model.
The first step was to create a fire patch classifier from scratch. The second step was to train a whole picture classifier and then apply a fine-tuned patch classifier if the image included fire. When SVM-pool5 (Support vector machines) is compared to CNN-pool5, the accuracies reported are 95.6% and 97.3%, respectively, with a detection rate of 84.8%, indicating that the CNN-pool5 network is more accurate than the SVM-pool5 classifier.

According to Pragati's article, [3] the environment can be damaged by a forest fire, causing a large amount of loss. The Amazon forest recently saw a fire that lasted more than 15 days. This led in a massive loss that had a negative impact on diversity and world conditions. The wireless sensor networks aid in the detection of forest fires. It can issue a warning as soon as an uncommon event occurs. These networks may occasionally generate false alerts as a result of incorrect detection. Machine learning mechanisms can be utilised to prevent similar incidents in such instances. Previously, satellite-based techniques were employed to detect fire.
However, because it took photographs of the earth's surface every two days, it may be impossible to detect the distraction. As a result, it may not be regarded as a viable method. The quality of the images may also be altered by the weather. Watch towers were another means for detecting fires. It was handled manually by watching the entire woodland area from a tower and determining if any fires occurred. Another method involves the use of optical sensors and a digital camera. It would be ineffective because high trees or hills would distract the vision.

Aral describes how The amount of smoke produced by a fire can be used to detect it.[4] The smoke sensors are used to measure the amount of smoke produced by the fire, which is then compared to a threshold value, and if it exceeds that value, a fire scenario is declared. Fire can be spotted as soon as feasible using image processing. Installing CCTV cameras across the area, and the footage from these cameras may be processed to monitor the fire. If any changes occur, it is simple to notice and promptly extinguish the fire. When the alarm goes off, a water extinguisher is activated to extinguish the fire.The CCTV camera is used to record video of a specific location and is linked to a Raspberry-pi minicomputer. So that it might obtain continuous video capturing of a certain area. The acquired video images are evaluated frame by frame, and once a fire is detected, the alarm is activated. In addition, the alarm would be shut off after the fire was totally quenched. The Virtual Network Computing is utilised for programme execution, where video details are sent from the raspberry-pi to the watching PC. This system includes modules for detection, alert, fire extinguishment, software, and networking.

The colour of a camera image is extremely essential in fire detection. It is not always possible to view the whole forest photographs based on their size due to challenges in detecting fires.[5] As a result, adopting Convolutional Neural Network (CNN) technology would make it easier to avoid blindness and increase the accuracy of fire recognition. For picture categorization, it employs the support vector technique. The image is split based on the colour of the flame and sent to the CNN network using this technique.This would discover more attributes and determine whether or not a fire occurs. The colour of the flame in a photograph can be used to detect fire. The intensity of the fire can be measured by counting the number of pixels projected in a picture according to the colour of the fire. As a result, it should be easier to identify and extinguish fires. A vast amount of data should be used to train and test the system. Algorithms are employed in image segmentation and fire detection. This way of recognising the fire should be more successful and reliable. The precision should be far superior to the other approaches. (Wang, Yuanbin, 2019)

Kim proposes a system that is modelled after a human fire detection system. [6] Faster R-CNN, a region-based method, is used to detect suspicious Points of Interest. Following the marking of the region of interest, the characteristics collected from the bounding boxes are transferred to the LSTM Long Short-Term Memory to determine whether or not there is fire in a short period of time. Faster R-CNN takes advantage of CNN's characteristics and introduces a region proposal network, which is utilised for mapping the features in the source image. It harvests features using the ROI pooling procedure and then classifies the object position based on the class scores.

Based on ensemble learning, an innovative method for fire detection is proposed. [7] The dataset was developed by combining 10581 pictures from public sources such as BowFire [8, FD-Dataset [9], ForestryImages[10], and VisFire[11]. To obtain greater accuracy than a single object detector, the dataset is preprocessed and supplied into not one, but two independent object detectors, YOLOv5 and EfficientDet, which are integrated in parallel mode. Although it employs integrated object detectors, it does not consider the entire image. As a result, another classifier is introduced to address this issue. EfficientNet analyses the image as a whole to ensure that the information is fully utilised. The outcomes will be determined by a decision strategy algorithm that considers the opinions of the three distinct object detectors, improving the model's performance and decreasing the number of false positives. According to this study, they have obtained a superior trade-off in terms of average accuracy, average recall, false positive, and latency.

Bowite proposes a method for real-time forest fire detection based on the wireless sensor network paradigm. This technology detects and forecasts fires more precisely than other methods used to detect forest fires. [8] First, the sensor networks collect information regarding humidity, smoke, temperature, and wind speed, all of which affect the forest fire. Sensor nodes are distributed across the forest and organised into clusters. The sensor nodes use GPS to track their location since they may relay location details together with data such as temperature measurements to the cluster head. The cluster header then computes the weather index using a neural network algorithm and delivers this information to the manager node. The wind speed is estimated through wind sensor nodes that are manually put throughout the forest. When an abnormal event happens, such as high temperature or smoke, the manager node notifies the users. In addition, the management node provides data regarding the levels of forest fire danger rate based on the weather index from various clusters. So that users can quickly determine the exact location of a forest fire if one happens. They may also safeguard the forest from fire hazards due to early identification (Liyang Yu, 2005).

A research technique use a light detection and ranging (LIDAR) device in conjunction with a neural network to identify forest fires. LIDAR is mostly utilised in environmental and atmospheric research. [9] A lidar is made up of a photo detector, a radiation emitter, a signal receiver, as well as signal processing hardware and software. The neural network is required in this case to train well with the Neyman-Pearson criterion. To achieve an accurate level of detection, the committee machine was trained with all possibilities, including false alarms, in the validation test sets. Neural networks are used to build these committee machines. Each committee machine is on duty, tackling substantial challenges in a recognition problem. Because different neural networks have varied capacities, they can be combined to find answers to difficult problems. Two distinct kinds of neural networks are involved in the instance of committee machines. One type of perceptron is a single layer perceptron, which has several nodes that receive signals and a neuron. The other employs a cascading architecture with two processing neurons, one connected to the preceding neuron and the other to the input nodes. As a result, autonomous identification of forest fires using committee machines and LIDAR is more useful than traditional methods (Vilar, 2003).

A research paper [10] suggests a system that detects forest fires by combining neural networks, computer vision rules, and other expertise criteria. This system is built utilising a variety of methodologies, including visual infrared image matching, past hazards memory, image processing, position, size, and geographical data. In this case, infrared cameras, visible cameras, and meteorological sensors are used to acquire input data. The image processing tool is used in conjunction with visual and infrared processing. Infrared processing consists of detection, oscillation, and alert processing. The false alarms are separated using the growing-region method. The visual processing procedure determines the precise position of the visual picture based on the infrared analysis method. It can be discovered and readily rejected by applying several techniques. Meteorological data is utilised to detect humidity, temperature, and other elements that cause forest fires. As a result, estimating the potential of fire is simple. This proposed method can detect forest fires at an early stage and eliminate false alarms (Begoa C. Arrue, 2000).

Deep learning and wireless sensor networks can aid in the identification of forest fires. [11] The study proposed a system that uses these approaches to identify forest fires in their early phases. Using the deep learning model, the system identifies fires based on data collected from several sensor networks distributed throughout the forest. The system in this case is made up of the Internet of Things as the basic concept, moving or fixed sensors, and an appropriate deep learning model. More precisely, many sensor nodes are placed inside each 1 km distance, and these nodes transmit data to internet servers via gateways. The acquired data is then shown in a dashboard with an internet network. Humidity, carbon monoxide, temperature, carbon dioxide, and air pressure are all measured at each node. These elements played a significant impact in the forest fire. This method first derives weather information from a weather detector positioned in the forest and then calculates the Fire weather index (FWI) utilising sensor nodes and deep learning algorithms and metrics. If the FWI's value changes, the Unmanned Aerial Vehicle (UAV) assists in detecting these sensor readings more accurately in order to detect the presence of fire. In addition, the control tower serves as a fire distinguisher (Wiame Benzekri1, 2020).

Another research paper presents an idea for the detection of forest fire using spatial data mining and image processing. [12] Firstly, the mining of spatial data occurs and then the digital image from these data is converted to YCbCr Color space and then divided accordingly to identify the areas with fire. A fuzzy set is generated for the fire areas with the values of color space. Color space means a creation, specification, and visualization of colours. The amount of red, blue, and green color determines a color in a computer system. This technology is used in this system. Data mining consists of database, pattern recognition, statistics, machine learning, and visualization techniques. The methods used for the segmentation and identification processes are anisotropic diffusion and the fuzzy logics. Using these rules and approaches, this system detects the forest fire using the spatial data accurately (Prof. K.Angayarkkani, 2009).

The authors of this research concentrate on developing a neural network fire warning system using sensor data.[15] Temperature, smoke density, and CO content are all measured by the sensor. The research proposes using a neural network to process sensor data. The decision-making system detects fire or smoke by continually scanning a single detector based on a threshold or limit.

For object detection, a radial basis function (RBF) network is used. It is a form of neural network that uses local approximations to generate local responses to input. According to the output of the network's hidden layers, the output is classified into fire, smouldering fire, and no fire. The results of this experiment reveal that this system obtained a rate of error of 2.3% chance of fire, 1.8% chance of tiny fire, and 1% chance of no fire. According to the authors, the network can increase its ability to adapt to various unanticipated scenarios. More improvements are offered by collaborating data from many sources.

The authors offer a low-cost fire detection method based on surveillance footage utilising CNN. [14] This article examines the statistics on fire deaths seriously. As a result, their primary goal is to develop a system that is both home-friendly and commercially viable. This study explains how to carefully pick data, as well as how to analyse computational complexity and detection accuracy. They extract features from photos using a model called GoogleNet. They lower dimensionality to reduce the complexity of larger patches. The model is validated using two independent datasets, and the results are compared. They achieved an accuracy of 93.5% on the first dataset and an accuracy of 86% on the second.

IV. PROPOSED FRAMEWORK

The suggested framework takes advantage of the benefits of computer vision and object detection algorithms. OpenCV accepts input via computer vision, preprocesses it, then pools it using an area of suggestions. The region-based object identification algorithm in YOLO then classifies those suggestions in the ROI as fire or non-fire.

A. Object Detection by You Look Only Once (YOLO)

You Look Only Once (YOLO) is a cutting-edge, real-time item detection system that is both fast and accurate. Prior detection systems detect by repurposing classifiers or localizers. They apply the model to an image at various scales and places. High-scoring image portions are considered detections. It takes a very different approach. It uses a single neural network to process the entire image. This network separates the image into regions and forecasts bounding boxes and possibilities for each. The projected probabilities are used to weight these bounding boxes. Compared to classifier-based systems, this has significant advantages. At test time, it examines the entire image, thus its prediction is informed by the image's global context. It also predicts with a single network assessment, as opposed to R-CNN systems, which take thousands for a single image. Because each grid cell only predicts two boxes and can only have one class, YOLO imposes substantial spatial limits on bounding box predictions. The number of nearby objects that our model can predict is limited by this spatial constraint. Our approach has trouble with little objects in groupings, such as flocks of birds. Its model struggles to generalise to objects with novel or unconventional aspect ratios or configurations since it learns to estimate bounding boxes from data..

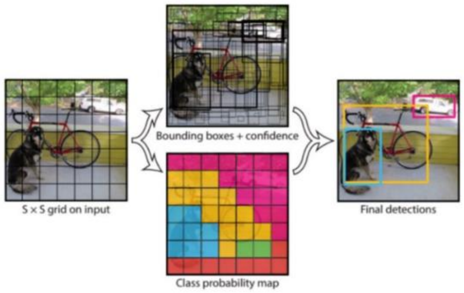

Fig 1. YOLO detection process

B. Architecture

YOLO's architecture is made out of solely one neural layer. YOLO is distinct from other object detection algorithms in that it can construct regions that are important in the original image using image transform filters known as bounding boxes. Other algorithms create the model using weighted sums and connection weights. In the feature maps, the pixel colour represents activation locations. The white and red pixels in the feature map correspond to points in the original image with high activation. Orange pixels indicate weak activation sites, while black pixels indicate significant negatives activation points. The fire region in the original image is reddish orange so the Computer Vision extracts the fire pixels. Convolutional neural networks are distinguished by their ability to share functions across layers. The network feature extractor is a

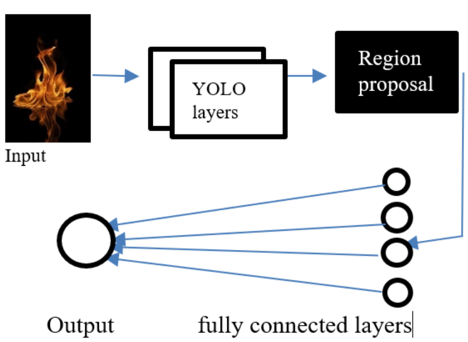

Fig 2. Architecture of YOLO for fire detection.

basic YOLO programme that allows for easy object detection in images. The simplistic architecture of YOLO is depicted in Fig 1.

The above graphic Fig.1 depicts the basic architecture of Convolutional neural networks; data is provided as input, in this case photographs of fire. The network's layers then abstract the image, removing any background noise and highlighting the object to be recognised. In the fully connected layers, the layers generate regions of proposals that are later integrated to construct a machine learning model, and the decision-making algorithm analyses the output from the layers to get a result.

VII. METHODOLOGY

The project's expected objective is to detect fire efficiently in real-time and photographs and videos, after which it sounds the alarm and sends incident reports to the appropriate authorities. The suggested system will be able to optimise itself by analysing the available hardware (desktop PCs or GPU servers) on which it is deployed. The suggested system will allow the end user to select from a library of photographs or videos from which to begin the detection operations. We anticipate that the project will evolve into a semi-functional element that can be placed on current satellite monitoring systems or data relay centres to provide as many eyes in potential fire breakout areas as possible.

The stages include *A. Acquisition of Dataset, B. Data Preprocessing, C. Feature Extraction, D. Building model, E. Validation and testing.*

A. Acquisition of Dataset

Data is in the form of video frames gathered from CCTV footage and photos and videos received from Kaggle and other free sources, but specially generated movies will be utilised to perform training and testing for convenience of use. Collecting such recordings with fire is a time-consuming operation. The frames with and without fire are then saved as follows. The dataset is then divided into two parts: training and testing. This must be done with extreme caution because if the data provided to the neural network is distorted, the outputs will be corrupted and the system will fail to generate an accurate system.

B. Data preprocessing

The next step in creating a high-quality machine learning model is data preprocessing. The data is cleansed and processed here, or it is simply made fit for usage. Data preparation is the process of eliminating sounds and other undesired elements from a frame. The algorithm must be fed relevant data or it will yield undesirable results.

C. Feature Extraction

For the neural network to detect fire accurately, it must first understand the characteristics of fire and how it appears in the computer's vision. The human eye can easily identify the feature of fire. Fire emits a reddish colour and takes on diverse shapes and motions depending on the fuel it burns. The shape, colour, and velocity of fire and smoke are used in this study to detect them. We extract the characteristics from the training set's various frames. In the object detection, which is powered by a YOLO method, the neural network collects these features using a feature extraction network. These video frames are sorted into fire and non-fire conditions after the features are extracted. The characteristics are retrieved using picture descriptors and bounding boxes.

D. Building the model

The extracted features are then passed to the network to build a model. This model is a set of thresholds to help the network to accurately detect fire. The model learns from the features extracted and set a standard for analyzing new input data. s.

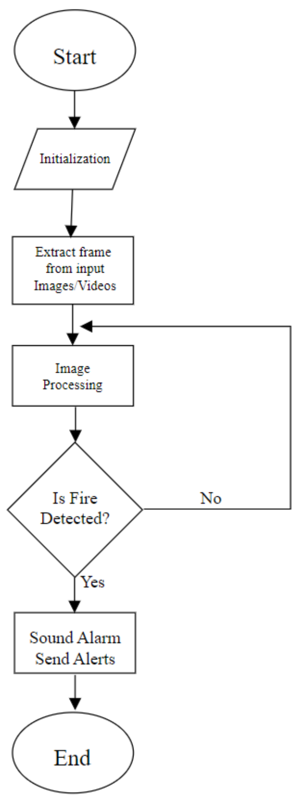

Fig 3. Flowchart For Proposed System

E. Validation and testing

Validation of the machine learning model is critical because accuracy and system functionality are clearly vital. The validation phase is carried out using a different set of video frames that is completely different from the dataset used to develop the model. According to the results of the tests, the system obtained approximately 73% accuracy with the validation set.

VIII. EXPERIMENTATION RESULTS.

IX. The project's findings are really satisfying. The system identified fire with a 72% accuracy rate. In comparison to previous neural networks, the results obtained show potential for the implementation of Convolutional neural networks for detecting fire. With a fully linked network, the system intelligently mixes different training data sets to calculate and reduce false alarm rates. The data is then sent to a decision-making algorithm, which determines whether or not there is a fire. Despite small detection problems in certain photographs, the overall performance and statistics are excellent. The main disadvantage is that it is a little slow because it requires more computer resources to generate results. By cleaning the data more thoroughly, the false alarm score can be lowered. The rate of false alarms should be maintained to a minimal when implementing.

X. CONCLUSION

The application of utilizing video frames in the detection of fire using machine learning is both demanding and inventive. It is possible to prevent damage and loss due to random fire accidents by using Surveillance systems if this system with a low mistake rate can be applied on a large scale, such as in major enterprises, households, and woods. The proposed system can be upgraded by merging wireless sensors with CCTV for increased protection and precision. The algorithm shows considerable promise in terms of adjusting to different environments..

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