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Using Convolutional Neural Networks and Deep Learning Models for Forest Fire Detection and Protection

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Abstract:-

Devastating natural catastrophes of unfathomable scale are caused annually by hundreds of forest fires throughout the world. A plethora of well researched options are either waiting to be tested or are already in use to address this issue. To find out where the fire is, people are using sensors. However, extensive forest areas do not meet this condition. Using state-of-the-art technology, we provide a novel method for fire detection in this article. More specifically, we suggested an AI platform. Recognition and detection of smoke and fire using computer vision echnologies, fed by still photos or video data from cameras. One way to determine the fire's intensity is via a "convolution neural network," a deep learning technique. Because of this, forest video surveillance systems will be able to deal with more complicated real-life circumstances. The accuracy is determined by the datasets, the method we will employ, and the separation of the datasets into a train set and a test set.

Index Terms:- Topics covered include fire detection, picture categorization, deep learning, OpenCV, and CNNs.

1.INTRODUCTION

Forests play a crucial role in maintaining Earth's delicate ecological balance. Regrettably, it is often only after the forest fire has spread across a considerable region that it is noticed. causing it to be difficult, if not impossible, to control and halt. Devastating loss and permanent damage to the ecosystem and climate are the results. Forest fires contribute 30% of atmospheric carbon dioxide (CO_2) and release massive volumes of smoke and carbon dioxide (CO_2), which harm the ecology. The standard practice is to put a stop to illicit logging. The system's objective is to detect potential threats by continually capturing forest noise, then determining the character of each segment based on processing of the recorded signals [1]. Rapid deployment of sufficient fire apparatus and trained operational personnel to the scene of the fire is of the utmost importance. In addition, there has to be a well-developed system in place to ensure that fire extinguishers are readily available, regularly serviced, and monitored for any signs of fire. Combining early detection with remote sensing techniques, logistics, training through simulation, and firefighting vehicles is the basis of an integrated approach to forest fire detection and suppression. The size of the area, the risk of wildfires, and the presence of humans all dictate the specific detection systems that should be used. These days, WSNs, or wireless sensor etworks, are an integral part of the ever-growingpopular systems for the Internet of Things (IoT). The environmental monitoring industry may also reap the benefits of such systems, which have a wide range of applications. their creativity. Analog and digital sensors, signal processing algorithms, and the Raspberry Pi Model 3 form the basis of an intelligent forest environment monitoring system. We use sensors to keep an eye on things like soil humidity, temperature, and gas concentrations, all while we analyze ambient noise. [2] in The three fully-connected layers and the final 1000-way softmaxn are monitored by forest fire automation, which uses blocks of functional circuit and sensor modules integrated as a unit. We used a newly-developed regularization algorithm "dropout" to significantly decrease overfitting in the fully-connected layers. For the purpose of forest fire prediction, researchers have compared a number of machine learning methods, including regression, decision trees, neural networks, and more. [8] In order to determine whether a forest zone is high-, medium-, or low-active, semi-supervised rule-based classification models are seldom used [8]. Early detection and prevention of fire propagation are crucial in preventing forest fires from becoming uncontrolled and spreading over large areas. A holistic, multi-pronged strategy that allows for constant situational awareness and rapid response is required to combat these catastrophes. Using state-of-the-art technology, we provide a novel method for fire detection in this article. More

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specifically, we suggested an AI platform. Recognition and detection of smoke and fire using computer vision echnologies, using either still photos or video input from cameras. A "convolution neural network" is a deep learning technique that may be used to determine the quantity of fire.

2. RELATED WORK

2.1The basic tenet of traditional fire detection has been the identification of visually distinguishing characteristics in fire photographs. Changes were examined by Chen [7]. using a rule-based method for firing decision-making and an RGB and HSI color model that is based on the difference between successive frames. Using the specific forest in question, Celik and Demirel [5] suggested a general rule-based scenario. The majority of esearchers(33%) use WSN for tracking applications, while nearly half(48%) use it for data exchange inside their system and almost half(43%) use it for data transfer between sensor nodes. [4] In order to enhance the accuracy of both training and classification, a robust AdaBoost (RAB) classifier is suggested. [5] Classification of flame pixels using the YCbCr color model to separate chrominance and luminance components; the neural network has 60 million parameters and 650,000 neurons. It is composed of five convolutional layers, some of which are followed by max-pooling layers; three fully-connected layers; and a final 1000-way softmaxn layer. Wang [8] also used an HSI color model to identify the potential fire region from a picture, and then they computed the flame color dispersion to pinpoint the exact location of the fire. Nevertheless, a number of environmental variables, including illumination and shadow, may compromise color-based fire detection systems. Using more characteristics such the area, surface, and border of the fire area to color, Borges and Izquierdo [9] used the Bayes classifier to identify fires. An optical flow-based fire detection system was suggested by Mueller [10] utilizing a neural network. The technique uses a merging of two optical flow models to differentiate between static and moving targets. Also, a multi-expert system that takes into account the color, shape, and motion characteristics of a fire was suggested by Foggia [11]. Texture, form, and optical flow are other characteristics that may help limit erroneous detections, but they are not enough on their own. However, these methods aren't great at reflecting the spatial and temporal information involved in fire settings, and they need domain knowledge of flames in collected images—which is crucial for exploring hand-crafted features. Furthermore, almost all systems that rely on the traditional methodology just use a static picture or consecutive pairs of frames to identify fires. As a result, they fail to take into account the fire's longer-term dynamic behavior in favor of its more immediate effects.

2.2 A Method Based on Deep Learning Object identification, picture classification, audio recognition, and natural language processing are just a few of the many recent successful applications of deep learning. Several deep learning-based fire detection investigations have been carried out by researchers in an effort to enhance performance. In comparison to more traditional methods of fire detection that rely on computer vision, the deep learning technique offers a number of advantages. One advantage is that the traits aren't hand-picked by a human but rather learned by the network itself via extensive and varied training. So, instead of focusing on finding the right handmade features, you should focus on building the right network and getting the training data ready. The fact that the features and detector/classifier may be trained in the same neural network at the same time is another distinction. Consequently, with an effective training algorithm, the importance of the correct network architecture grows. Sebastien [12] suggested a CNN-based fire detection network that trains features using a neural net classifier of the Multilayer Perceptron (MLP) type all at once. A CNN-based cascaded fire detection approach was also suggested by Zhang et al. [13]. According to their approach, a global image-level classifier examines the whole picture first; if a fire is identified, a fine-grained patch classifier is used to pinpoint the exact locations of the affected areas. A CNN fire detector that has been fine-tuned was suggested by Muhammad et al. [14] for use in a fire monitoring system. This design is a convolutional neural network (CNN) architecture that takes its cues from the Squeeze Net [15] design and uses them to efficiently detect, localize, and analyze the fire scenario from a semantic perspective. The activation of a CNN unit in the deep layer may be thought of as a feature that carries a great deal of context information due to the unit's broad receptive field. Among the many benefits of using CNN-learned features for fire detection is this. Locating objects has also been an issue, despite CNN's much better categorization performance compared to conventional computer vision approaches. To find SRoFs and non-fire items, such as smoke and flames for SRoFs and other things unrelated to the fire for non-fire objects, the suggested technique uses an object detection model. Because of differences in shadow and light, anything unrelated to the fire might trigger more false alarms; for example, it could pick up on red clothing, red cars, or a sunset. Even though it is not limited to the object detection model, we use the Faster R-CNN model to identify fire objects. Convolutional neural network (CNN) feature extractors, a localizer with a classifier, and finally the deep object detector often make up a single- or multi-

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stage system. Consequently, our object detection model has a feature extractor that can acquire additional contextual information and has a comparatively broader area of receptive field compared to the detected SRoF region. Even while convolutional neural network (CNN) methods work quite well, they can't capture fire's dynamic behavior, which can only be captured by RNNs. Hochreiter and Schmidhuber [16] presented LSTM, an RNN model that addresses the issue of RNN vanishing gradients. LSTM's memory cells store internal states and repeated behavior, allowing it to collect temporal characteristics for decision making. Nevertheless, decision-making relies on capturing long-term dynamic behavior, which may be challenging when the number of recursions is restricted. Decisions based on LSTM's long-term behavior must, therefore, be carefully considered. By extracting CNN characteristics from optical fluxes of successive frames and temporally accumulating them in an LSTM network, Hu et al. [17] recently used LSTM for fire detection. The merging of consecutive temporal characteristics forms the basis of the ultimate judgment. But instead of utilizing RGB frames directly, their method calculates the optical flow to prepare the CNN input. This study takes advantage of the best features of the real-time fire detection methods that have been reviewed so far—such as convolutional neural networks trained on video sequence frames—and combines them with proximity detection of fires using a USB camera. The goal is to combine the training and test data of fire signatures in order to detect and notify fires early on, and to help fire rescue teams navigate to the scene of the fire so that they can respond appropriately. The assessment of fire detection systems brought attention to some inherent flaws, but this unique approach of utilizing cameras and video processing addresses such issues.

3. SYSTEM DESIGN AND DEVELOPMENT

3.1. TOPIC: THE SYSTEM A high-level summary of the fire detection system's software implementation and hardware module design appears in figure 1. Figure 2 shows the various parts of the fire detecting unit's hardware. Computers may now function as videophones or videoconferencing stations thanks to webcams, which record video and connect to computers or networks using video connections (often a USB port). Security monitoring and video file recording are only two of the many uses for webcams with computer video telephony applications. In its most basic form, it is an Arduino Uno running the Convolutional Neural Network (ConvNet/CNN) algorithm for fire detection, together with a USB camera and some kind of communication or open CV module. In order to provide data into the CNN program, the microcontroller periodically polls the sensors. Management information systems (MISs) notify the building's inhabitants and the closest fire station of a potential fire if the system detects fires. It falls back to using the short message service (SMS) in the event that the data connection fails to transmit the message. Everything from the USB camera and arduino microcontroller board to the software that runs the CNN fire detection algorithm and controls the device is part of the fire detection unit. The software subsystem is the non-physical component of the fire detection unit. It is responsible for receiving web camera inputs, analyzing them using open CV image processing, and sending out alarms when flames are detected. One such library is OpenCV, which stands for "Open Source Computer Vision." Its primary goal is to facilitate image processing and real-time computer vision. Its primary function is to do all operations pertaining to images. Machines can see everything and can translate visual information into numerical values with the help of pixels.

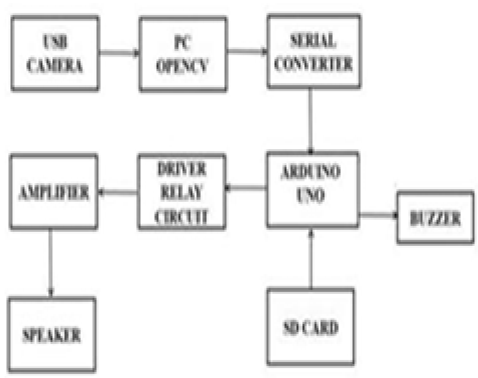

Figure1. Block Diagram of Fire detection system

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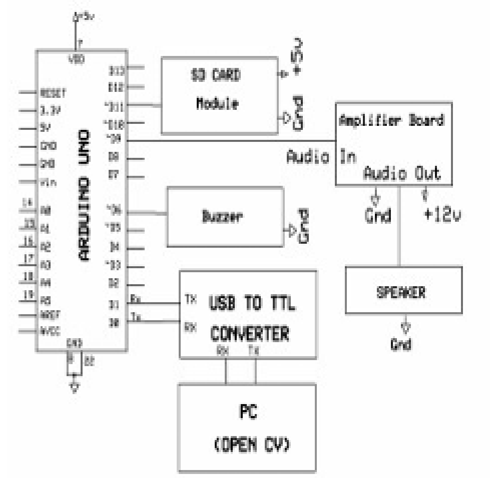

Figure 2. Circuit diagram of Hardware circuit

3.1.2. Neuronal Correlates: One kind of deep learning method is the convolutional neural network, or CNN. recognize a picture, categorize its elements according to their relative significance (using learnable biases and weights), and distinguish between them. Unlike other classification methods, ConvNets don't need as much pre-processing. With sufficient training, CNN can learn these filters and properties, in contrast to rudimentary approaches where filters are hand-engineered. Figure 3 displays the CNN architecture. Multiple three-dimensional planes make up the network's levels. With its many neurons per 3-dimensional plane, convolutional neural networks (CNNs) are well-suited to process picture input. The CNN's input layer, which is a three-dimensional matrix, is where the picture data should be stored. The feature extractor layer, which is a component of the Convolution layer, is linked to a portion of the picture in order to calculate the dot product of the receptive field and the filter and to execute the convolution operation. Interposed between two convolution layers, a pooling layer reduces the input image's spatial volume after convolution. A hyperparameter called "Filter" and a stride parameter are present (S). Neurons, weights, and biases make up a fully linked layer. It bridges the gap between neurons in different layers of the brain. Through training, it is able to categorize photos into many groups. The last CNN layer is the Softmax or Logistic layer. It is located at the very bottom of the FC layer. For multiclass binary classification, logistic is the way to go. is the purpose of softmax

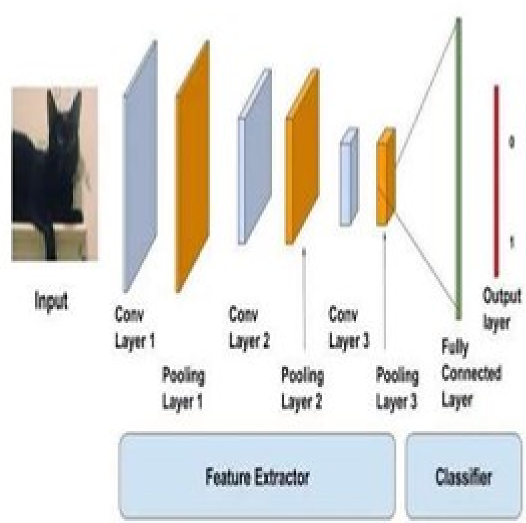

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Fig3. Structure of CNN

4. SYSTEM ARCHITECTURE SYSTEM IMPLEMENTATION AND TESTING

The input data is processed using several kernels of varying sizes to create feature maps in a convolution operation. ext, these feature maps are fed into method called sub sampling or pooling, which involves selecting the most activations from a narrow region. These tasks are crucial such that feature vectors may be reduced in dimension and translation invariance can be achieved, up to a point. Part of the CNN pipeline that is as crucial is completely linked layer, where input data is used to simulate high-level abstractions. Neurons in the convolution and fully on nected layers learn and modify their weights during training to better reflect the input data. This is one of the three fundamental activities. Software and hardware work together to form the system architecture. Part of the hardware is the fire detection system, which is where the software is installed. One component of the hardware system is a surveillance camera unit, which can detect fires more effectively. This device can keep an eye on the premises all the time and transfer the footage to a central server.

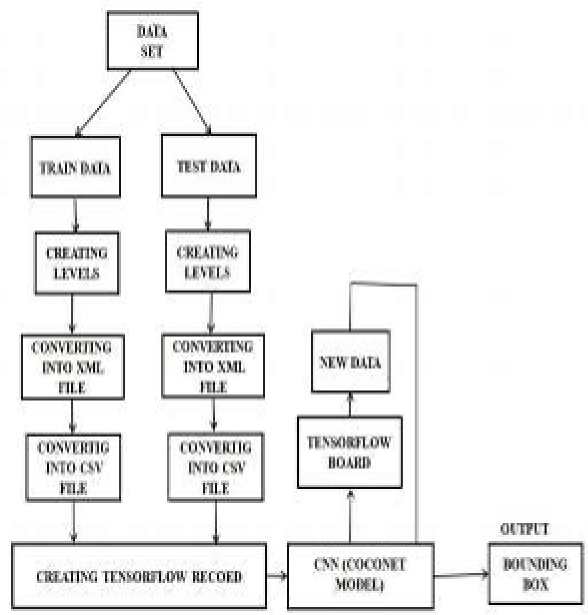

Figure 4: Flow diagram for fire detection softwareBuilding the object detector will help train a trustworthy classifier. plethora of photos, all shot in different ways, are needed. Therefore, it's critical that they've different lighting situations, a range of backgrounds, and unstructured objects. The samples' different fire classifications are shown in

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Figure 5: Sample images for classes.

Approximately 80% of the photos should be sent to the object detection/images/train directory, while the remaining 20% should be transferred to the the directory located at object detection/images/test. We need picture labeling software of some kind to categorize our data. One of the best ways to classify images is via labeling. The "Create RectBox" button may be used to generate the bounding box. When the bounding box is ready,and then save the picture with your annotations. Every single picture in the test and training folder has to go through this procedure again. Incorporating photographs in order to train the object detector, we must first generate TFRecords that have labels. Two scripts from Data Tran's raccoon detector will be used to build the TFRecords. We may utilize the code we have generated to test our newly constructed object detector. When a fire is detected, the alerting system is activated because the video stream from the surveillance camera is transferred to the server, where the CNN model is run on the data.

5.SYSTEM IMPLEMENTATION AND TESTING

The convolutional neural network was trained using more than a thousand photos showcasing both fire and non-fire hazards. Online picture databases were used to compile the data. information aggregators. As you can see in Figure 5, we employed convolutional neural networks with several sample photos. Neural network training relies on separating the dataset into two parts, the training set and the testing set. The model was trained using test video streams, which were fed into the system as input. Classifier produces probability for the "fire" and "no fire" categories. The classifier's output is the set of classes that have the highest probability score. Google's Tensor Flow was used to construct the classifier module. One of Google's open-source software libraries, Tensor Flow allows users to do numerical computations using data flow graphs. A classifier with 94% accuracy was obtained after training the network on the data. Preprocessing the video stream and extracting frames from it are the first steps in the classification process. In order to ascertain the state of the region, the retrieved frames/images are categorized.

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6.RESULTS AND DISCUSSIONS

Presenting an easily deployable technique to an embedded device is the ultimate goal of this endeavor, which aims to construct a whole fire detection unit. Thus, it's necessary to use a test dataset that contains real-world fire emergency photographs captured using low-cost hardware, such as an Arduino Uno microcontroller, in order to ensure accurate results.the ATmega328P is the basis of the board. The video classifier did very well in the classifier module testing. With the goal of reducing the frequency of false alarms When event occurred, a confidence threshold for the classifier was setup. Therefore, the alert will only go off if the confidence is higher than or equal to the threshold. The objective is to swiftly and accurately identify fires in the live video feed and sound the alarm. By removing all superfluous nodes from the module, the classifier's performance was increased using TensorFlow's "optimize_for_inference" script. The script performs additional optimization procedures, such as inserting normalization operations into the convolutional weights, which enhance the model's performance.

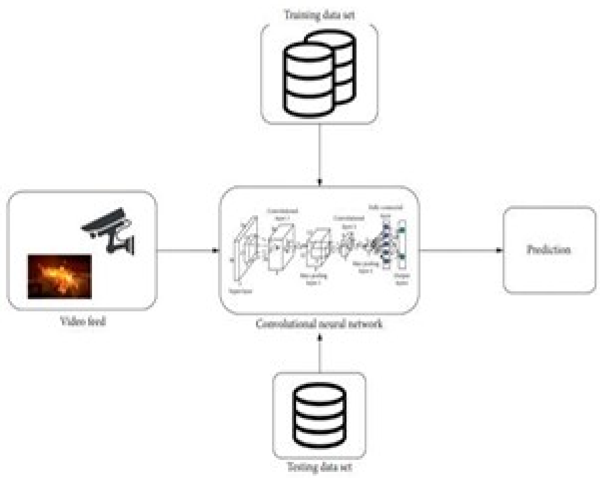

Figure 6: Video processing unit on a dedicated server.

7.CONCLUSION AND RECOMMENDATION

We introduce a Convolutional neural network (CNN) trained on a varied dataset and constructed entirely from scratch. The end goal of the whole The goal of this project is to create an IoT-enabled fire detection system that can take the role of traditional physical sensor-based systems while simultaneously eliminating or greatly reducing the issues related to delayed and false alarms. An inexpensive embedded device, such as the ATmega328P-based Arduino Uno microcontroller board, can operate the presented neural network at 24 frames per second with no hiccups. The model's accuracy as measured on both a conventional fire dataset and a custom-built test dataset that includes difficult real-world fire and non-fire photos with image quality comparable to the images acquired by the Arduino camera. Additionally, the detecting device may provide the user visual feedback and a fire warning in the event of a fire emergency thanks to the IoT feature. The accuracy of flame detection was enhanced by this study; nevertheless, there is still a need for more research in this area due to the large amount of false alarms. And it's possible to fine-tune the existing flame detection frameworks so that they can spot fires with more intelligence. Because of this, forest video surveillance systems will be able to deal with more complicated real-life circumstances.

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