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Multi-Classifir Fire and Smoke Detectior Using Deep Learning

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Abstract : - Fire is one of the most destructive powers that has been a double-edged sword. Although it is highly beneficial and provides energy when it is handled in an effective manner, it can be quite lethal if it is allowed to continue unchecked. Combustion, as well as the conversion and release of energy, is what makes fire so destructive. It is a violent process that has the potential to unleash enormous amounts of harm. This is a very unfavorable condition that has the potential to result in a truly catastrophic event. A great number of species of flora and fauna have become extinct as a result of the recent years, which have been marked by a big number of disastrous wildfires that have resulted in a large scale loss of life and property. This is one of the most deadly occurrences that has occurred in recent years. The most significant issue is that there is not yet a fire detection method that is both efficient and practical. Consequently, the purpose of this study piece is to propose an efficient multi-classifier strategy for fire detection. This approach identifies the color of the fire, the form of the fire, and the movement of the fire, in addition to the detection of smoke through the use of the convolution neural network. According to the extensive experimental results that demonstrate the superiority of the suggested multiclassifier fire and smoke detection strategy, this approach has shown to be one of the most effective approaches for fire detection. This is obvious through the fact that it has been one of the most effective techniques

***Key Words*: — Convolution neural network, Multi-classifier, Fire shape, Fire Motion , Fore color, Temporal effect**

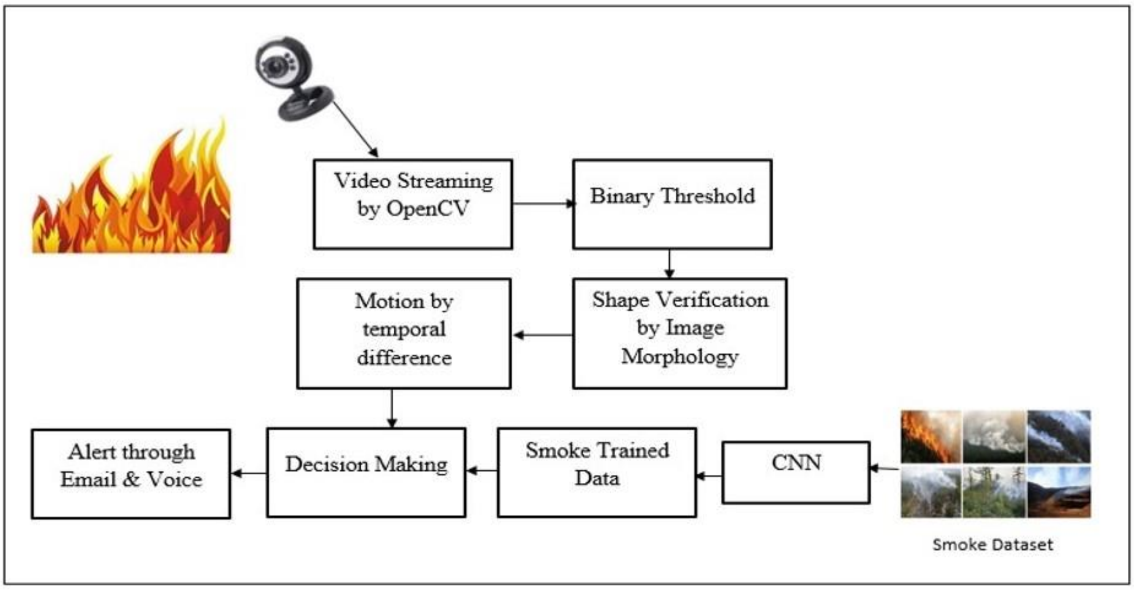
I. INTRODUCTION

Despite the fact that fire safety appears to have become a main concern in our contemporary lifestyles, there are still fire threats that have the potential to result in considerable loss of both property and personal resources. As a direct result of this, the utilization of a fire suppression system was necessary in both the preparation before the fire and the response to it. The primary objective of both automatic fire detection methods would be to identify a fire, notify and relay messages to residents in an acceptable manner, and consult with first emergency workers in order to equip them with knowledge. The manner in which these objectives are accomplished is determined by the specific conditions, which may include the norm of the geographical location in question. At the opposite end of the spectrum, detection systems are not novel; they have been available for a considerable amount of time. The early 1800s saw the development of a significant number of the earliest alarms. The mechanism consisted of two different fire alarm systems, one of which required 9 a telegraphic key, and the other of which required a lever. It would have been necessary for someone to approach inside one of the devices and turn the lever in order to send a notice to a nearby alarm station in the event that a fire was discovered in a residential or commercial establishment. Following the transmission of the signal to a coordinator at the site, the coordinator would then contact the fire brigade to request assistance. It was a lengthy process that needed to be completed in multiple stages. Since then, the fire detection system has also undergone advancements in accordance with the progression of technology. Throughout history, 7 fire alarm systems have been considered to be among the most significant components that are present in everyday life. In the long run, it will be one of the primary goals of the technology that controls smart homes with its capabilities. The components of a fire alarm system are designed to work in conjunction with one another in order to identify and notify the user in both audible and visual ways in the event that smoke, fire, or other harmful situations arise. It is also possible that it will contact the emergency services in order to receive monitoring from all of the fire detection devices in the vicinity. At the moment, that is the state of affairs that exists. In many countries, a fire alarm system is 11 one of the most common types of security systems that are required to be installed in every establishment, including homes and businesses. The device has the capability of providing homeowners with advance notice and notification in the event of a probable fire. [1] S. Li, Q. Yan, et al. explain how convolutional neural networks can be successfully applied to computer vision tasks to improve the efficiency of computer vision-based fire detection. Nevertheless, in certain difficult settings, the performance of existing CNN-based techniques is still restricted. Because of their enormous model sizes, most of them are challenging to implement on embedded vision devices with limited resources. The author suggests a multiscale feature extraction, implicit deep supervision, and channel attention mechanisms based fire detection solution to address these issues. [2] In this research, CHANGJUN FAN ANDFEIGAO et al. describe 10 a wireless body area network-based system that uses two readily available devices—a smart watch and a smartphone—to mine inertial sensor data from both devices in order to detect smoking incidents. After data preprocessing, an end-to-end trainable united model is developed in the system by merging a random forest with a variational autoencoder 15 to classify the collected data into smoking and nonsmoking categories. [3] Z. Xu and et al. To meet these increasingly strict requirements and surpass existing re detection approaches, the author's work develops a novel re detection method employing variational autoencoder (VAE) and deep Long-Short Term Memory (LSTM) neural networks. The author uses high-fidelity simulations and datasets from real-world re and non-re experiments supplied by NIST to assess the efficacy of the method. The performance of the author's suggested re-detection is compared and discussed with that of alternative techniques, such as the conventional LSTM, the cumulative sum control chart (CUSUM), the exponentially weighted moving average (EWMA), and two heat detectors that are currently in use. [4] A thorough analysis of YOLO architectures, such as 4 YOLOv5, YOLOv6, YOLOv7, YOLOv8, and YOLO-NAS, for smoke and wildfire detection is presented by E. Casas et al. The author's goal is to evaluate how well they work in early wildfire detection. Performance indicators including recall, precision, F1-score, and mean average precision are used in this, and the Foggia dataset is used. The author's approach trains every architecture across 300 epochs, with a particular emphasis on recall due to its applicability in this field. In order to gauge real-world performance, the "best models" are assessed using the Foggia test set and then put to the test again using a demanding, specially built dataset sourced from reputable websites. The findings demonstrate that in both testing and validation, 4 YOLOv5, YOLOv7, and YOLOv8 provide balanced performance across all measures. In this study report, the section under "Literature Survey" looks at past work that has been done. The third section provides an in-depth analysis of the methodology, while the fourth section concentrates on the evaluation of the results. In the final section of this report, Section 5, we arrive at a conclusion and provide some suggestions for further research..

OBJECTIVES:

1 .Collection of live video frames.
2. Color identification through best channel.
3. Alert rising for Wild Fire and Smoke only.
4. Alert by Voice, Email methods.

II..PROPOSED METHODOLOGY



Proposed model Overview

This section of the study article primarily focuses on outlining the specifics of thesuggested model that is used for the multi-classifier and CNN supervised model deployment of the fire detection model. The detailed explanation of the deployment system's steps is provided below.

Step 1: Video streaming - The first step is video streaming, which is primarily concerned with sending images from the installed webcam to the system that has been established.The suggested system installs the open CV, which is based on Java, to integrate the produced project source code with the current camera hardware. Video from the camera is streamed into the instance media player with the aid of opencv. Subsequently, a frame is captured at each predetermined time and saved in both the designated location and an instant queue.

Step 2: Binary Threshold (Color classifier) - In order to determine the fire color, an instance thread retrieves one image frame from the queue in this phase. In this process, each pixel in the image is scanned to get its signed integer value, which varies depending on the color that exists. This signed integer number is used to right shift 16, 8, and 0 bits, respectively, to extract the corresponding RGB values. The RGB value produced for each pixel is next subjected to an estimation of its average values. The RGB values are set to (255,255,255) in order to turn the pixel white if the average value that is obtained is higher than the specified threshold value. On the other side, by setting the RGB values to (0,0,0), the pixel is made to seem black. This is because, in a picture such as fire, bright pixelsalways have an RGB value that is closer to 255 than it is to 0, otherwise 0. Following the conversion of the image's pixels into white and non-white, the fire pixels appear white while the remaining pixels are black. A black-and-white binary picture is produced by this method. The algorithm 1 below indicates the technique mentioned.

.ALGORITHM:

Binary threshold for Fire detection using color component
// Input: Video Frame F
// Output: Fire detected image
Step 0: Start
Step 1: Get Image path.
Step 2: Get Height and width of the Image F (L*W).
Step 3: FOR i=0 to width.

Step 4: FOR j=0 to Height.
Step 5: Get a Pixel at (i, j) as signed integer.
Step 6: Convert pixel integer value to Hexadecimal to get R, G, and B.
Step 7: AVG=(R+G+B) /3
Step 8: IF AVG >T (T is Threshold)
Step 9: Pixel at (i,j) is FIRE
Step 10: ELSE
Step 11: Pixel at (i, j) is NOT FIRE
Step 9: End of inner for
Step 10: End of outer for
Step 11: Stop

Step 3: shape verification- The binary image acquired, wherein fire is represented by white pixels and the remaining pixels are black, is employed to construct a coaxial ratio array 8 for the purpose of indicating the fire's shape. The procedure involves estimating the ratio of each white pixel position with respect to a specific axis in order to generate an array representing the fire shape of a given frame. The array containing the instance frame is compared to the array of the subsequent frame in order to quantify the alteration in the fire's shape. 7 In the event that the alterations in the shape array or co-axial array above the predetermined threshold, the instance frame is deemed to possess a positive fire. The equations 1 and 2 can be used to represent the morphology or co-axial ratio. Subsequently, the frame undergoes an estimation of the fire motion in the subsequent stage.

Where M(x) – Morphology vector related to X axis. M(y) – Morphology vector related to Y axis. P(i,j) – Pixel at position i and j

N – 21 Number of pixels in the image

Step 4: Motion by Temporal Effect- This represents the third stage of the color categorization process used to identify fires based on motion. The technique involves listing the instance frame for the fire pixel position, and subsequently comparing this list with the previous list to determine the absolute difference. If the disparity exceeds the predetermined threshold, the frame is designated as the fire. The aforementioned procedure is represented by the algorithm 2.

Algorithm 2: Fire Detection by motion

// Input: Time T, Frame Fc, Frame Fp, Threshold Fire pixels Th
// Output: Fire Detection through motion
Step 0: Start
Step 1: WHILE (TRUE)
Step 2: for each time T
Step 3: Fp → Fc
Step 4: calculate pixel positions of Fp in an vector Vp
Step 5: calculate Pixel positions of Fc in an vector Vc
Step 6: IF ABSOLUTE DIFF (Vp –Vc) > Th
Step 7: Label Frame for Fire
Step 8: END IF
Step 9: END WHILE
Step 10: Stop

IV.RESULT AND DISCUSSION :

The proposed methodology has been implemented using the Java and python programming language, employing the NetBeans and Spyder Integrated Development Environment as the designated Integrated Development Environment (IDE). The efficacy ofthe proposed approach has been assessed, and to achieve this objective, a comprehensive set of assessment measures has been implemented using the following tests outlined below.

The system's evaluation was conducted using publicly accessible fire photos obtained from the URL: http://mivia.unisa.it/datasets/video-analysis-datasets/fire-detection-dataset/. Our approach utilizes many sorts of photos to locate fires, as depicted below.

V.CONCLUSION

Within the scope of this project, the approach that has been offered 6 for the detection of fire and smoke has been precisely defined. There has been 17 an increase in the number of fires that have been particularly lethal, which has resulted in a rise in the number of livesn lost, as well as the loss of biodiversity and property worth billions of dollars. 18 When it comes to mitigating this undesired phenomena before it is too late, it can be rather challenging to have any success. Therefore, for this aim, an efficient and prompt detection of fire 10 is of the utmost importance in order to significantly reduce the number of occurrences of these incidents. In order to accomplish this goal, an efficient multi-classifier strategy has been defined in this research work. This approach identifies the fire 8 as well as the smoke in order to achieve prompt identification of the fire. For the purpose of achieving the frames in which the fire needs to be detected, the approach makes use of a video stream. Following the utilization of these frames for color detection through the utilization of binary threshold, the temporal difference is evaluated for the purpose of identifying the motion of the fire, and ultimately, the determination of the form of the fire isvalidated through the utilization of morphology. The smoke detection strategy, which is accomplished through the utilization of convolutional neural networks, is a supplement to the multi-classifier approach that is being utilized here. The comprehensive evaluation methods have been of critical importance in demonstrating the superiority of the methodology that has been proposed. It is possible that the future course of study will involve 10 the use of this method in cameras with a lower resolution in regions such as dense rainforests and other crucial locations for the detection of wildfires.

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