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Original article

Video Based Fire Detection and Alert System

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Abstract

Effective fire detection is crucial for safeguarding lives and property. Fires pose not only direct risks but also economic damage, especially in the case of forest fires. Traditional fire detection systems rely on electronic sensors that detect heat, smoke, or other fire-related characteristics, but their accuracy can vary based on proximity. To overcome this, video-based fire detection methods have been carried out in this paper. One approach uses the HSV color model, applying a color mask and intensity threshold to identify fire pixels in video frames. The other approach employs deep learning with the Inception V3 CNN model, training it on fire and non-fire images to identify the video frames. While both methods provide real-time detection, the deep learning method, which captures complex patterns for greater accuracy, is more sophisticated than the HSV-based method in terms of simplicity. Choosing between the two depends on requirements and available resources. Video-based fire detection shows promise and warrants further research for system enhancement in different scenarios.

Keywords: HSV, Deep Learning, Gaussian Blur, Binary mask.

I. Introduction

Forest fires and fire-related accidents may have catastrophic impacts on the environment and the economy. Traditional fire detection methods using electronic sensor devices have limitations in precision and coverage. In this paper, we are implementing two real-time video-based fire detection systems, namely HSV-based system and Deep Learning-based system. The HSV-based approach utilizes pure image processing techniques to detect fires in videos. It applies color thresholding to identify fire regions and triggers preventive actions if the size of the fire region exceeds a threshold. These actions include email notifications and alarm sounds. Alternatively, deep learning models, such as Inception V3, are used for accurate fire detection. The model has been altered for this specific application. This method highlights the implementation, and performance, demonstrating its effectiveness in real-world scenarios. By using video feedback and AI, this system offers a more reliable and accurate approach to fire detection, potentially preventing the loss of lives and property. It provides wider coverage, enables early detection, and can be customized for various settings and industries. Although the system might have higher operating costs than traditional sensors, its reliability and security compensate for the increased expenses. Integration with existing video feedback mechanisms, like CCTV cameras, can reduce costs. Overall, this project aims to mitigate the risks and impacts of fires by improving fire detection accuracy and response capabilities.

II. Literature Survey

Borges and Izquierdo propose a real-time fire detection method using visual information alone. From video frames, they extract color and texture information. and calculate the probability of fire presence in a region using a probabilistic model. Bayes' Theorem is employed for probability estimation, trained on labeled images of fire and non-fire regions. The model classifies regions according to the calculated probability, achieving high accuracy in detecting fire in real-world videos. However, a drawback is the method's reliance on particular features that could not be consistently present or easily extractable in certain fire types or challenging video conditions, potentially affecting the method's performance in those cases [1].

T. Zaman et al. in their work "Fire Detection Using Computer Vision" presents a technique for detecting fire in video data through computer vision methods. The approach involves identifying motion regions in the video and extracting fire-colored pixels. To confirm the presence of fire, a wavelet transform is applied to analyze the various characteristics of the extracted pixels, including intensity and frequency of change. By tracking the growth rate of the fire region, the technique distinguishes between controlled and unstable fires. Evaluation of the method shows a true positive rate of 85.57% and an average detection delay of 6.62 seconds for hazardous fire at a frame rate of 10 frames per second. The outcomes show how well the suggested method works for precisely identifying and classifying fire. The wavelet transform is a versatile mathematical tool widely used in image and video processing, signal processing, and data compression to enhance accuracy and efficiency in various applications [2].

Sruthi, S. et al. in their work "Block Motion Estimation Based Fire Detection" presents a real-time fire detection method using motion estimation based on image processing techniques. The proposed method utilizes block motion estimation to identify upward movement in consecutive video frames, followed by image processing.

And HSV color grading to identify frames resembling fire. A machine learning algorithm is then employed to determine the presence of fire. The method offers benefits such as real-time fire detection, irrespective of the fire's distance from the camera, and the ability to detect fires in remote locations where traditional sensor-based systems may not be effective. However, the method has limitations, including dependence on block size and distance from the camera, as well as the possibility of false alarms caused by non-fire-related movements. The paper includes a literature survey comparing various fire detection approaches, highlighting the potential of motion estimation-based techniques in overcoming the limitations of traditional systems and machine learning-based methods. Further research is suggested to explore the effectiveness of this approach [3].

Kim, B et al. in their work "A Video-Based Fire Detection Using Deep Learning Models" describes a technique that integrates Faster R-CNN and LSTM for fire detection in video sequences. Faster R-CNN is used for object detection to identify fire zones based on spatial features, while LSTM captures dynamic fire behavior by accumulating features over time. Short-term fire decisions regarding detection are made by a two-stage LSTM network, and a final decision is obtained through majority voting. The method also calculates flame and smoke areas to interpret fire dynamics. Experimental results show improved accuracy compared to other methods. Benefits include mimicking human perception, accurate detection of flame and smoke, and robust long-term decision-making. However, drawbacks include the need for ample training data, potential delays in real-time detection, and limitations in certain environments. Overall, the suggested technique has the potential to increase the accuracy of fire detection, but careful consideration of its benefits and limitations is crucial for successful implementation [4].

Sathishkumar, V.E. et al. in their work "Forest Fire Detection Using AI-Based Computer Vision Techniques: A Study on Transfer Learning with Learning without Forgetting (LwF)" introduces a novel approach to forest fire detection using transfer learning with LwF. The authors emphasize the importance of early fire detection in mitigating natural disasters and global warming. They employ Convolutional Neural Networks (CNNs) to detect fires and smoke from images and explore the use of pre-trained models to enhance accuracy while reducing computational complexity. The study also investigates LwF to preserve pre-existing classification abilities during network training for a new task [5].

III. Methodology

A. HSV Approach

The HSV model is often used in image processing to describe colors in terms of hue, saturation, and value, which makes it a suitable choice for detecting fire. By applying a color mask to each video frame, the model can isolate pixels that fall within a specific color range associated with fire. The color mask can be adjusted to achieve optimal detection performance based on the environment and lighting conditions.

Once the color mask has been applied, the values obtained from it are summed up to determine whether the magnitude of the fire surpasses a predefined threshold. If the threshold is exceeded, the system triggers an alarm to alert relevant personnel of the fire. Additionally, an email alert is sent to notify designated contacts, providing an additional layer of safety and security. The use of a thresholding function enables the system to differentiate between fire and other sources of heat, such as light bulbs or sunlight, ensuring that false alarms are minimized. This fire detection method is relatively simple yet effective, making it a practical solution for environments where quick response times are critical. The use of the HSV color model, combined with a thresholding function, provides accurate and reliable detection of fire, while the alarm and email alert features enable prompt response and communication in the event of a fire. Fig 1. illustrates the flow of this approach.

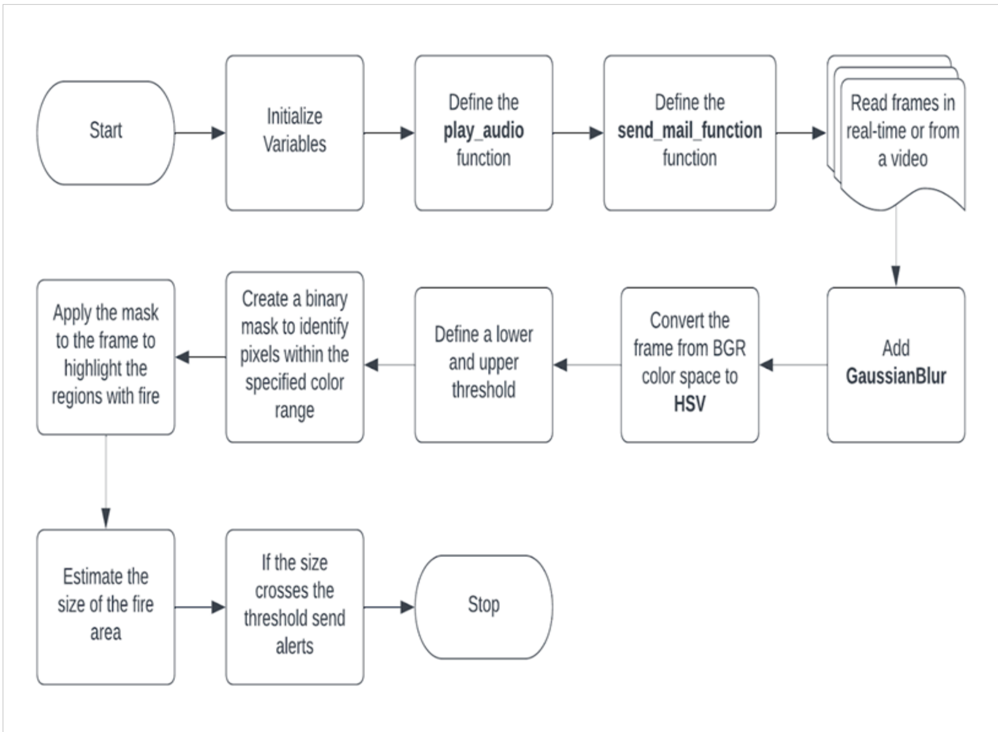

Fig. 1. Flowchart of HSV Approach

The play audio function and send mail functions wrap the code required to send out alerts when the threshold defined is exceeded. Once these are defined, the video feedback is read and converted to frames. Following this, each frame goes through a series of image processing steps. The steps are frame resizing, adding Gaussian blur, converting each frame from BGR to HSV, and creating and applying a binary mask. Let us understand why these steps are performed.

Frame Resizing: Resizing each frame to a desired width and height is an essential step to ensure that all frames are consistently processed and displayed. It also reduces the computational requirements for subsequent operations, making the system more efficient. By having uniform frame sizes, the system can operate more consistently and accurately, providing reliable results for real-time fire detection.

Gaussian Blur: Gaussian blur is a common image processing technique that is used to smooth out the details in an image and remove any high-frequency noise. By convolving the frame with a Gaussian kernel, it reduces the effects of small variations in the pixel values that could lead to false positives. The choice of kernel size depends on the image resolution and the desired level of smoothing. Gaussian blurring is especially useful in fire detection, as it can help remove small background variations and highlight the overall shape and magnitude of the flames.

Color Space Conversion: Color Space Conversion is an essential step in fire detection because it simplifies the detection process by isolating and detecting specific colors or ranges of colors. The conversion from BGR to the HSV color space is particularly helpful because it separates the intensity and color information, making it easier to detect colors associated with fire.

Binary Mask: After defining the lower and upper thresholds for the color range, the binary mask of the frame is created. The pixels within the color range are marked with the specified color, while the rest of the pixels are set to black. The binary mask obtained is then applied to the original frame. This results in an output frame where only the regions containing the fire, as highlighted by the binary mask, are retained. All the other pixels in the image are masked out, which reduces the visual noise in the frame, and focuses the attention on the regions where there might be a fire. This masked frame is then used for further processing to determine if there is indeed a fire in the image.

Fire Area Estimation: The fire area estimation step involves counting the number of non-zero pixels in the binary mask generated in the previous step. This pixel count provides an estimate of the size of the potential fire area in the frame. By comparing this size against a predetermined threshold value, the algorithm can determine whether the fire is significant or not. If the fire area exceeds the threshold, it indicates the presence of fire.

Following the above steps we get the size of the fire in the frames. Once the threshold is exceeded the fire is detected and the alerts are sent out.

Deep Learning Approach

In this approach, a pre-trained Inception V3 model is utilized for the detection. However, the model is customized and trained on fire and non-fire images so that it learns for this specific application. Let us look at the steps involved.

Dataset Selection: The process of selecting a dataset for fire detection involves choosing a collection of images that encompasses a variety of both indoor and outdoor fires. This selection is done with careful consideration to ensure that the dataset is diverse and includes a broad range of scenarios that represent different lighting conditions, backgrounds, and types of fires.

Preparing the Dataset: To prepare the dataset for fire detection, the chosen dataset was split into two subsets: a training set and a validation set. To enhance the accuracy and generalization ability of the model during training, data augmentation techniques were applied to the training dataset. The aim was to generate additional examples of fire images that could help the model learn to detect fires in a broader range of scenarios. Techniques such as horizontal flipping and zooming were used to generate new training examples that were similar to the original images but had variations in orientation, scale, and perspective.

Model Selection: To benefit from deep learning techniques for fire detection, the InceptionV3 model was selected as the base model. InceptionV3 is a well-known convolutional neural network (CNN) model that has been pre-trained on a large-scale dataset (ImageNet) and has proven to be highly effective in various image recognition tasks. Its pre-trained architecture significantly reduces the amount of training required for the model to learn to detect fires accurately. By fine-tuning the model on the fire detection dataset, we can transfer its high-level features to the task of fire detection, allowing it to identify fires in various real-world situations accurately.

Customization: The InceptionV3 model was customized for fire detection through a series of important modifications. Firstly, a global spatial average pooling layer was added to reduce the spatial dimensions of the feature maps generated by preceding convolutional layers, capturing crucial features while reducing computational complexity. Subsequently, dense layers were introduced to enable the model to learn non-linear relationships between extracted features and fire presence. To avoid overfitting, dropout layers were strategically placed between the dense layers, randomly deactivating neurons during training and improving the model's generalization ability. Finally, a softmax-activated dense layer with two output classes (fire and non-fire) was appended, facilitating the final classification of input images based on the presence of fire. This comprehensive customization process resulted in a more effective and interpretable fire detection model.

Training the Model: During the training phase, the newly added layers were initialized and trained while keeping the pre-trained layers frozen. The training was performed over 20 epochs, with batches of training images presented to the model during each epoch. By the end of the training process, the model had optimized its internal representations and could differentiate between fire and non-fire images with high accuracy.

Fine-tuning the Model: Fine-tuning the model involves adjusting the parameters of a pre-trained model on a new task. In this case, after training the added layers, the model's fine-tuning stage began. Fine-tuning the model's pre-trained layers is critical for achieving high accuracy and ensuring that the model is capable of generalizing well to new, unseen data. It allows the model to update its learned features to the target task while preserving the knowledge it gained during its pre-training phase.

Evaluation: The evaluation phase is crucial to assess the effectiveness of the trained model. In this paragraph, the effectiveness of the fire detection model is assessed using various metrics, including accuracy and loss.

Testing with Real Scenarios: To evaluate the model's performance in real-life situations, we used a webcam feed. Each frame from the webcam was passed through the trained model for fire prediction. If the model identified a fire in a frame, the color of that frame was changed to black and white, creating a visual highlighting effect that makes it easier to identify frames containing the fire. When the fire is detected the alerts are sent out.

IV. Results and Discussions

In this paper, we have explored two approaches for fire detection using video footage: one based on the HSV color model and the other utilizing deep learning with the Inception V3 Convolutional Neural Network (CNN) model. Each approach has its benefits and drawbacks, but both offer valuable contributions to fire detection systems.

The HSV-based approach provides a simple and efficient solution for fire detection. By applying a color mask to the video frames and using a threshold function, the presence of fire can be determined in real-time. The HSV approach may not capture complex patterns and variations associated with fire as effectively as the deep learning approach, but it offers a reliable and straightforward method for fire detection. On the other hand, the deep learning approach utilizing the Inception V3 CNN model leverages the power of neural networks to achieve higher accuracy in fire detection. By training the model on a large dataset of fire and non-fire images, it learns patterns and features associated with fire, enabling it to classify video frames as containing fire or not. This approach has the potential to capture complex patterns and variations of fire, thus increasing the accuracy of fire detection.

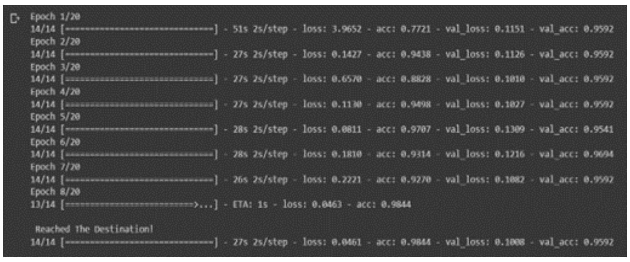

Fig. 2: Training the Model

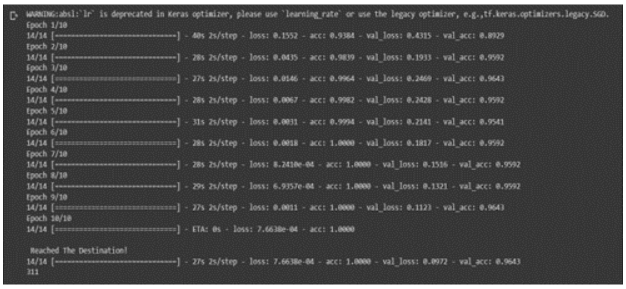

Fig. 3: Fine-tuning the Model

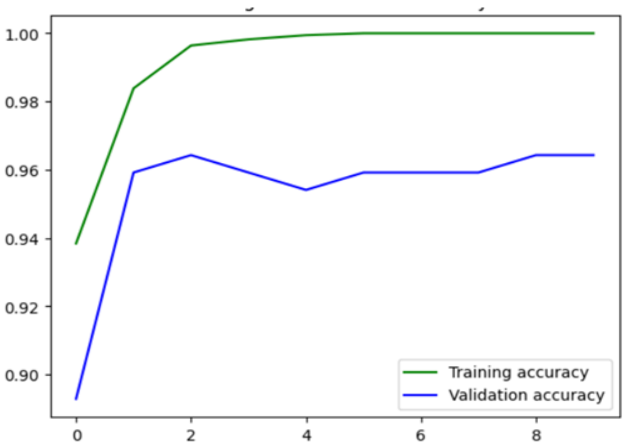

Fig. 4: Training and Validation Accuracy

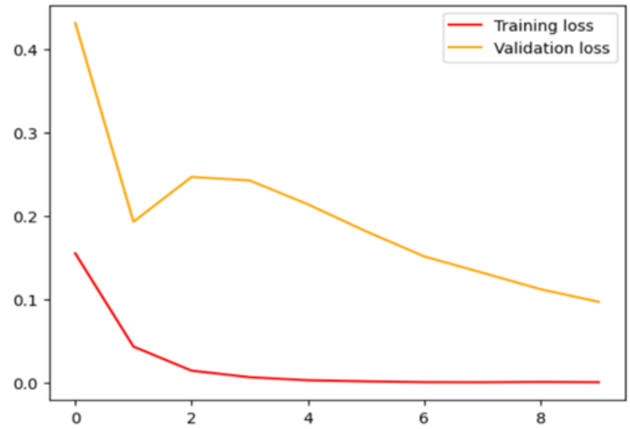

Fig. 5: Training and Validation Loss

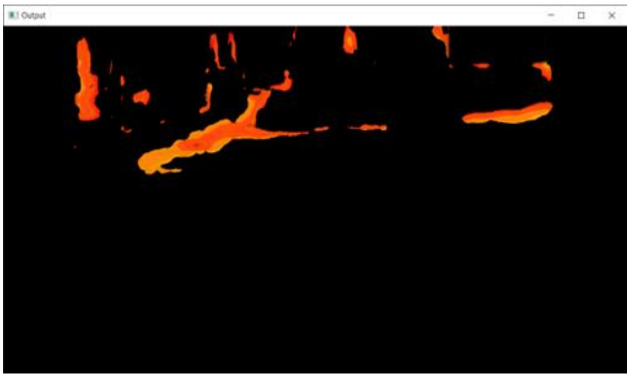

Fig. 6: Example of Fire Detection Using HSV Methodology

Fig. 7: Example of Fire Detection Using Deep Learning Methodology

V. Conclusion

Utilizing video footage for fire detection presents a promising alternative to traditional sensor-based systems. The proposed approaches provide different trade-offs between simplicity and accuracy, catering to different requirements and constraints. Both the HSV-based and deep learning methods have their merits, and future research can focus on further improving their performance and exploring additional techniques to enhance fire detection systems in various scenarios.

Selecting one of the two methods depends on specific requirements and constraints. If a higher level of accuracy is required, and computational resources and time are not major constraints, the deep learning approach may be preferred. It offers the potential for improved accuracy by capturing complex fire patterns. However, if real-time detection and simplicity are prioritized, the HSV-based approach provides a reliable method for immediately detecting fires in video footage. Further research and development can lead to even more effective fire detection systems that can better protect people and property from the dangers of fires.

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Dr. Ashwini S Savanth received her doctoral degree from Visveswaraya Technological University, Belgaum in 2023. She is currently working as an Associate Professor in the Dept. of E & C, BNMIT, Bangalore. Her areas of interest are Signal Processing, Machine Learning, Deep Learning, Pattern Recognition, and Neuroscience. Her research work was to study the effects of Rajayoga meditation on the human brain. Her interest in scientific studies of spirituality has led to contributions of multidisci-plinary research papers and with further research she wishes to contribute to the well-being of society.

Akasha T is an engineering graduate from BNM Institute of Technology, specializing in Electronics and Communication Engineering. His academic journey has equipped him with comprehensive knowledge in Data Science and Machine Learning. Driven by a keen interest in research, he is dedicated to exploring cutting-edge advancements in the field and making significant contributions to the world of technology.

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