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Smoke-Eye An AIML Based De-Smoking and De-Hazing System

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Abstract: Indoor fire incidents pose significant challenges to first responders, often due to the presence of smoke and haze, which severely limit visibility. Delays in response times and increased risks to both responders and victims are common consequences. To address this critical issue, the "Smoke-Eye" project introduces an AI-ML based de-smoking/de-hazing system designed to enhance visibility during indoor fire hazards. The primary objectives of "Smoke-Eye" include the development of a smoke and haze detection module, the implementation of advanced image dehazing algorithms, and the optimization of video processing.
Keywords: Smoke-Eye, de-smoking, de-hazing, Smoke, Haze

I. INTRODUCTION

Indoor fire incidents are fraught with danger, often compounded by the presence of smoke and haze, which drastically diminish visibility. This impairment can lead to delayed response times, increased risks for both responders and victims, and hampered rescue operations. In response to this critical challenge, the "Smoke-Eye" project is introduced —a pioneering AI-ML based de-smoking/de- hazing system. The system's foundation lies in robust data collection, annotation, and preprocessing. It employs state-of-the-art detection algorithms, such as YOLO and Mask R-CNN, and integrates advanced dehazing techniques, including the Dark Channel Prior. Rigorous testing, collaboration with firefighting and rescue teams, and continuous monitoring and maintenance are integral to the project. Ethical considerations, legal compliance, and knowledge sharing efforts ensure the system's reliability and integrity. "Smoke-Eye" represents a pioneering effort to improve visibility during indoor fire incidents, ultimately enhancing the safety and effectiveness of rescue operations. This project exemplifies a commitment to leveraging advanced AI and computer vision to address critical challenges in emergency response, with the potential to save lives and safeguard communities

II. LITERATURE REVIEW

Here we provide a brief literature on the various machine learning algorithms that were used in comparisons or analyzed individually for the purpose of smoke/Haze detection.

A. An end-to-end deep learning approach for real-time single image dehazing

Image dehazing methods can restore clean images from hazy images and are popularly used as a preprocessing step to improve performance in various image analysis tasks. In recent times, deep learning-based methods have been used to sharply increase the visual quality of restored images, but they require a long computation time. The processing time of image- dehazing methods is one of the important factors to be considered in order not to affect the latency of the main image analysis tasks such as detection and segmentation. An end-to-end network model for real-time image dehazing is proposed.

B. Real-time fire/smoke detection based on CNN

This work presents a real-time fire and smoke detection using YOLOv2 Convolutional Neural Network (CNN) in antifire surveillance systems. YOLOv2 is designed with light- weight neural network architecture to account the requirements of embedded platforms. The training stage is processed of-line with indoor and outdoor fire and smoke image setsin different indoor and outdoor scenarios.

C. Fire Detection Methods Based on Deep Learning: Datasets, Methods, and Future Directions

Traditional fire-detection systems primarily rely on sensor-based detection techniques, which have inherent limitations in accurately and promptly detecting fires, especially in complex environments. In recent years, with the advancement of computer vision technology, video- oriented fire detection techniques, owing to their non-contact sensing, adaptability to diverse environments, and comprehensive information acquisition, have progressively emerged as a novel solution.

D. Single Image Haze Removal Using Dark Channel Prior

The paper introduces the dark channel prior method for single image haze removal, a fundamental approach in dehazing. It has been widely cited and forms the basis for many subsequent dehazing techniques.Based on the IASM, a fast single image dehazing algorithm is also presented. In this algorithm, by constructing a linear model between the transmission and the haze aware density feature, the transmission map can be directly estimated through a linear operation.

E. Image Dehazing Using Color-Lines

This paper proposes a dehazing method based on color-lines, addressing challenges in different scenarios. A large amount of haze in the fire scene greatly affects the survey on the scene for fire fighters. The intelligent fire control can greatly improve the fire rescue efficiency and reduce the casualty rate. In this paper, an algorithm based on the hardware conditions of the intelligent fire helmet platform is proposed, which improves dark channel prior. It discusses the algorithm's performance and compares it with other existing techniques.

F. A Review on Image Dehazing Algorithms

This review article provides an overview of various image dehazing algorithms, categorizing them based on their underlying principles. It discusses challenges and future directions in the field. First, the shallow features of the haze image were extracted by a preprocessing module. Then, a symmetric network structure including a convolutional neural network (CNN) branch and a vision transformer branch was used to capture the local features and global features of the haze image, respectively.

III. METHODOLOGY

Utilizing Convolutional Neural Networks (CNNs) for de-haze and de-smoke methodologies in fire detection represents a cutting-edge approach to enhance the accuracy and reliability of fire detection systems. Haze and smoke particles often obstruct the visibility of critical details in images, making it challenging to detect fires accurately. CNNs excel in image processing tasks, and their ability to automatically learn hierarchical features from data makes them well- suited for addressing the complexities introduced by haze and smoke.

In the de-hazing process, a CNN can be trained to recognize and remove haze-induced artifacts from images, restoring clarity and improving the visibility of fire-related features. This step is crucial for ensuring that the subsequent fire detection algorithm operates on clear and informative images. Similarly, the de-smoking phase involves training the CNN to mitigate the impact of smoke, which tends to obscure important visual cues. By enhancing image quality through de- hazing and de-smoking, the overall performance of the fire detection system can be significantly boosted.

The CNN-based methodology involves training the network on a diverse dataset containing images with varying levels of haze, smoke, and fire scenarios. This enables the network to learn robust features and patterns associated with fire under different environmental conditions. The trained CNN is then integrated into the fire detection pipeline, where it processes input images in realtime or near real-time, effectively enhancing image quality before subsequent fire detection analysis. The advantages of this approach include increased accuracy in fire detection by reducing false positives and negatives associated with obscured visual information. Moreover, the adaptability of CNNs allows them to generalize well to different environmental conditions, making them valuable for real-world applications where fire incidents may occur in diverse settings. Overall, the CNN-based de-haze and de-smoke methodology represents a promising avenue for advancing the capabilities of fire detection systems, contributing to improved safety and early response in fire-related emergencies.

In the implementation of a CNN-based de-haze and de-smoke methodology for fire detection, the network architecture plays a crucial role. Typically, a deep neural network with multiple convolutional layers is employed to automatically learn and extract features that are resilient to atmospheric interferences. Transfer learning can also be leveraged by utilizing pre-trained CNN models on large datasets, fine-tuning them specifically for the de-haze and de-smoke tasks related to fire detection. This approach often accelerates convergence and enhances the model's overall performance.

Real-time implementation of the CNN-based methodology involves deploying the trained model on edge devices or integrating it into surveillance systems. This facilitates quick and accurate decision-making, critical for timely response in emergency situations. Additionally, the system can be enhanced with features such as alert generation and localization of the fire within the image, providing valuable information for emergency responders.

A. System Implementation

1) Architecture diagram :

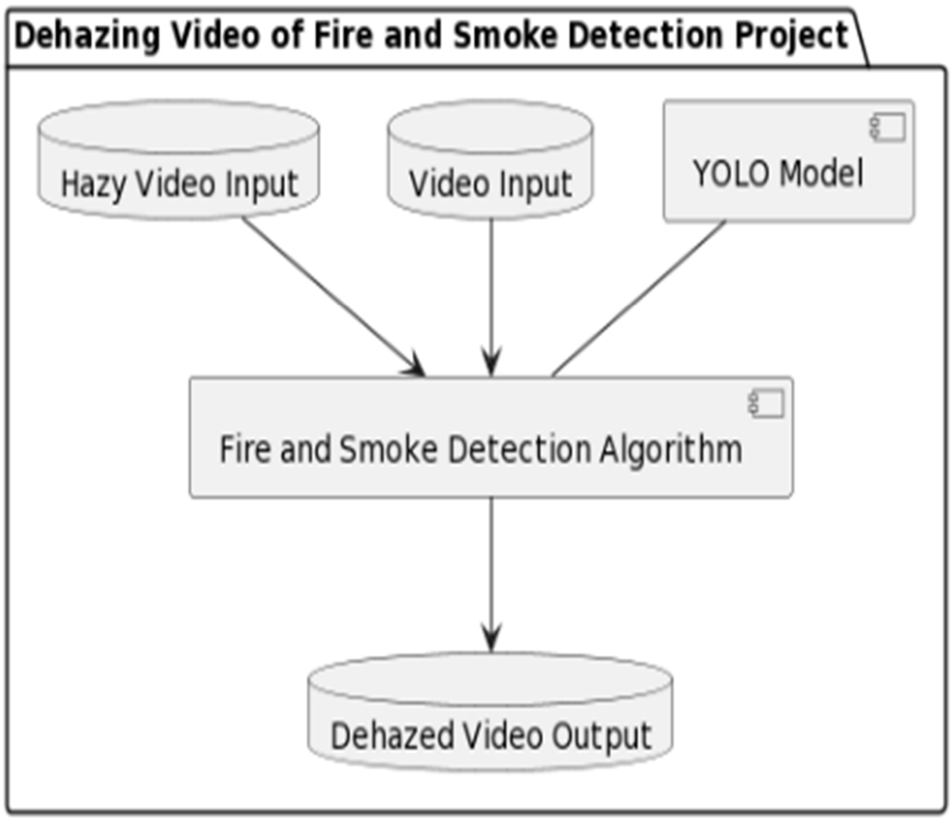

Fig.1 Architecture diagram

This component represents the YOLO (You Only Look Once) model, which is a deep learning-based object detection system.
YOLO is utilized in this project for detecting various objects, including fire and smoke, within the video frames.
Video Input:
This represents the original, non-hazy input video stream.
It serves as the primary source of video data for the system.
Hazy Video Input:
This component symbolizes a version of the input video stream that has been affected by haze or smoke.
In real-world scenarios, videos captured in environments with fire or smoke may suffer from reduced visibility due to haze, making it challenging to detect objects accurately.
Dehazed Video Output:
This depicts the output of the dehazing process applied to the hazy video stream.
The dehazing algorithm aims to enhance the visibility of objects within the video frames by reducing the effects of haze or smoke.
Fire and Smoke Detection Algorithm:
This component represents the algorithm responsible for detecting fire and smoke within the video streams.
It utilizes the YOLO model for object detection and operates on both the original video stream and the dehazed video stream.
By analyzing the video frames, this algorithm identifies regions containing fire and smoke, providing valuable information for fire detection and monitoring purposes.

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2) Dataflow Diagram:

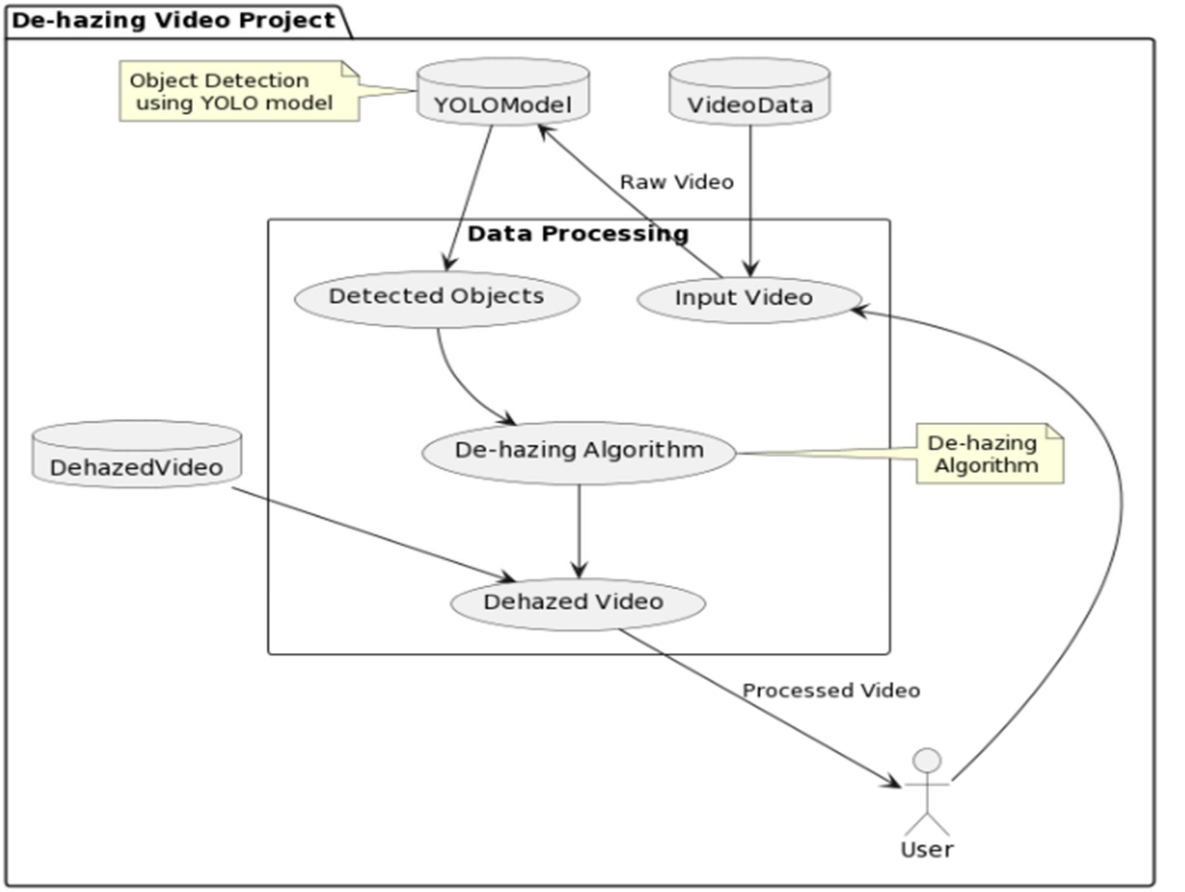

Fig.2 Dataflow Diagram

The overall process of the project involves the development of an AIML based dehazing and de-smoking model called Smoke-Eye, which utilizes Vision Transformers. The project lifecycle includes planning, development, testing, deployment, and maintenance phases.

Planning phase- The project focused on studying and implementing various key components such as shifted window partitioning schemes, nonlinear activation functions, and parallel convolution with attention. These components are crucial for enhancing the model's performance in dehazing tasks.

Development phase- the Smoke-Eye model is constructed with several improvements, including modified normalization layers, activation functions, and spatial information aggregation schemes. These enhancements are designed to optimize the model's effectiveness in dehazing and de-smoking technique.

Testing phase- Extensive testing is conducted on various datasets to compare the performance of Smoke-Eye with existing methods. The results demonstrate the superior performance of Smoke-Eye, with the large model achieving a PSNR exceeding 40 dB on the indoor set, outperforming previous state-of-the-art methods.

Deployment and maintenance phase- Deployment involves the implementation of the Smoke-Eye model for practical use in dehazing and de-smoking applications. The model's maintenance includes ongoing monitoring, updates, and improvements to ensure its continued effectiveness in addressing image dehazing challenges.

The project is based on Convolution Neural Networks (CNN) and the language used is Python

Use case diagram:

In this diagram,

The "User" interacts with the system by uploading an image.

The system consists of several use cases within the "Dehazing System" package:

Upload Image (UC1): The user uploads an image to the system.

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Preprocess Image (UC2): The system preprocesses the uploaded image before dehazing.
Dehaze Image (UC3): The system performs the dehazing process on the pre-processed image.
Display Dehazed Image (UC4): The system displays the dehazed image to the user.
Additionally, there are use cases related to fire and smoke detection:
Fire Detection (UC5): The system detects fire in the dehazed image.
Mark Fire Areas (UC6): The system marks areas in the image where fire is detected.
Smoke Detection (UC7): The system detects smoke in the dehazed image.
Mark Smoke Areas (UC8): The system marks areas in the image where smoke is detected.

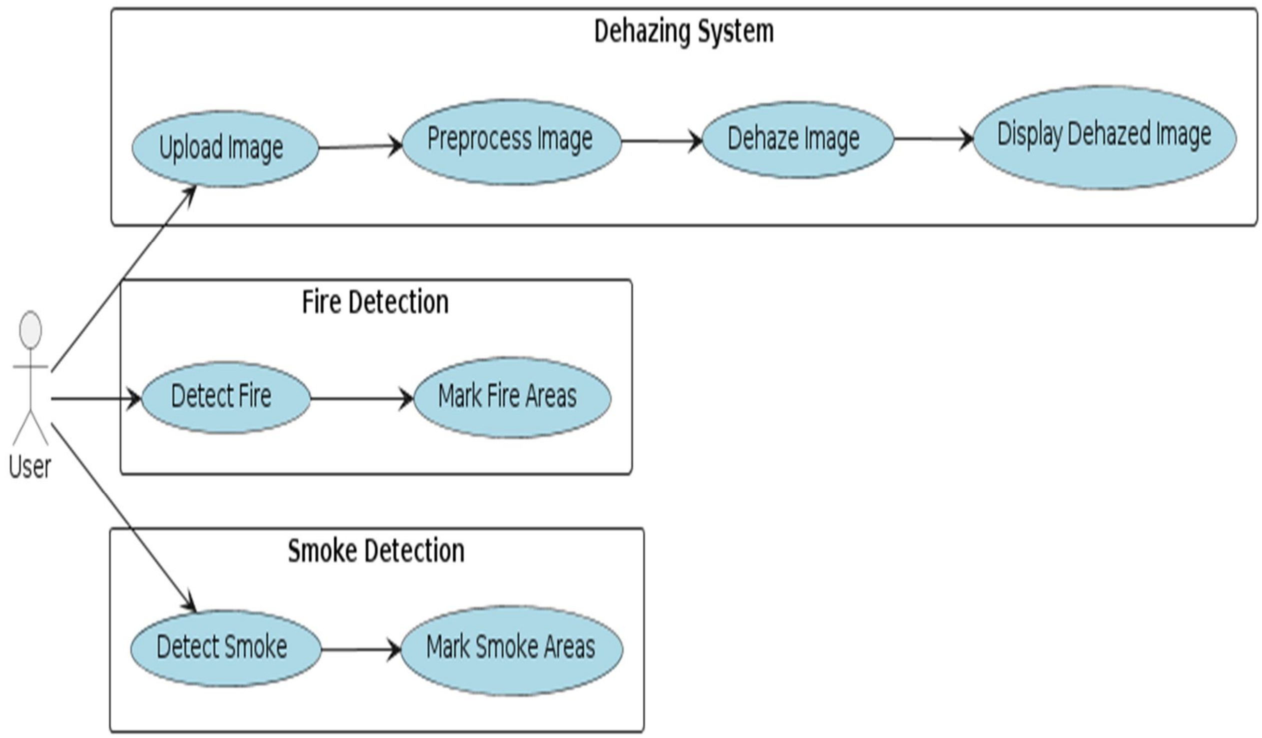


Fig.3 Use-Case diagram

Activity diagram**:**
This UML activity diagram outlines the steps involved in dehazing images of smoke and fire using YOLO:
Start Dehazing Process: Initiates the dehazing process.
Is Image Hazy?: Checks if the input image is hazy.
Yes: Proceeds to apply dehazing algorithm.
No: Skips dehazing and proceeds to object detection.
Apply YOLO for object detection: Utilizes YOLO for object detection.
If objects are detected:
Identifies smoke and fire regions.
Generates a mask for identified regions.
If no objects are detected, the process stops as no smoke or fire is found.
Apply Dehazing to identified regions: Applies the dehazing algorithm to the identified regions.
If dehazing is complete, it generates the enhanced image output.
If dehazing is not complete, it repeats the dehazing process until satisfactory results are achieved.
Stop: Ends the process.
This diagram illustrates the workflow of dehazing images of smoke and fire, integrating YOLO for object detection and applying dehazing algorithms to enhance the visibility of smoke and fire regions in the images.

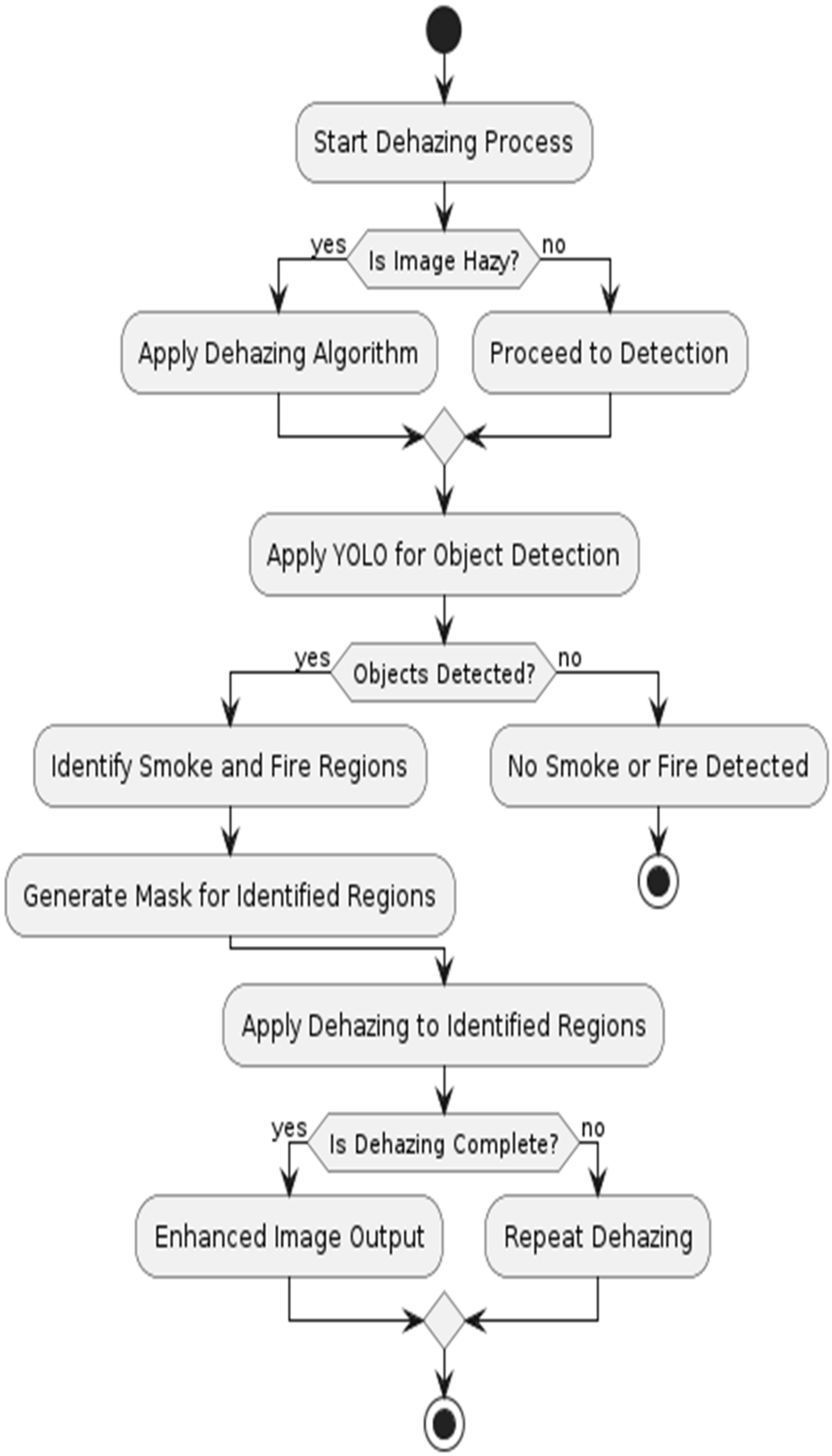
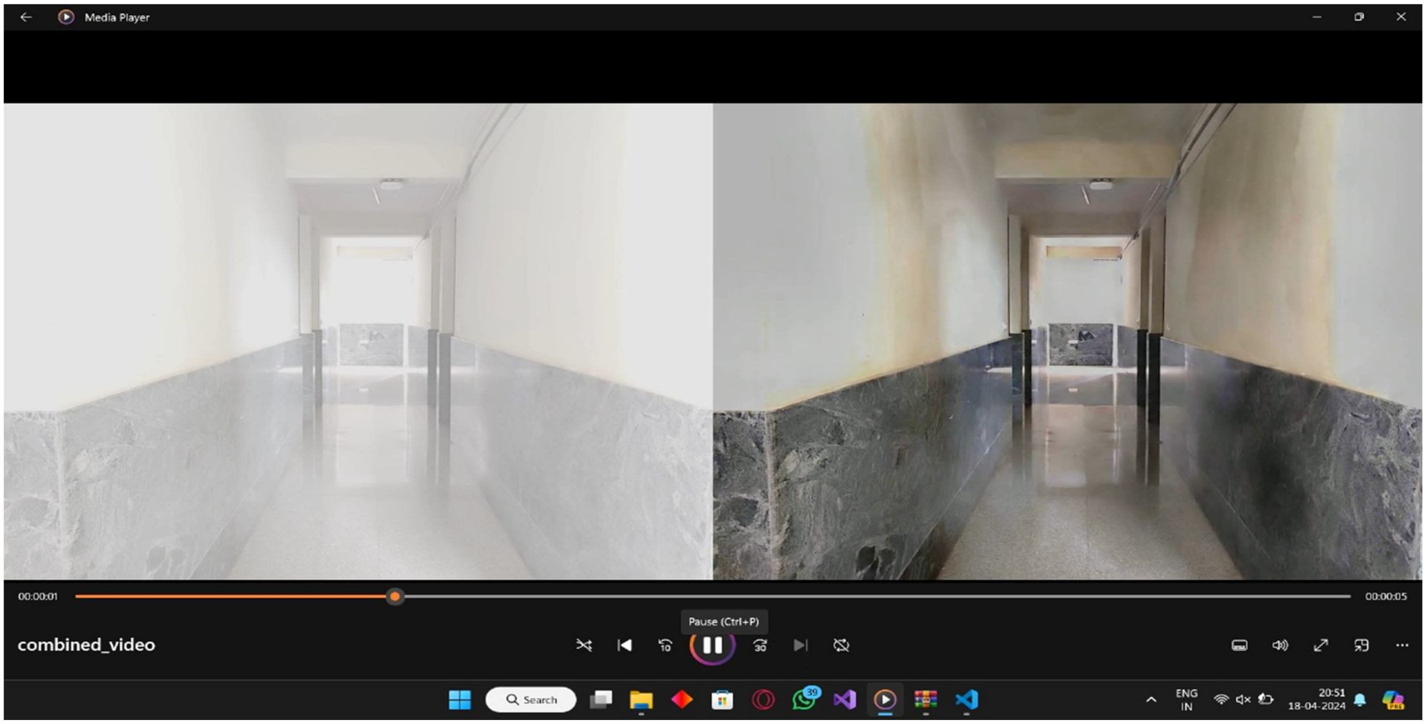


Fig.4 Activity diagram

IV. RESULTS



A. *Video Input and Pre-processing:*

Use OpenCV to read the input video.
Iterate through each frame of the video using a loop.

B. *Frame De-hazing:*

Preprocess the frame based on the model's requirements.
Load the trained model using chosen deep learning framework (PyTorch).
Pass the frame through the trained model to obtain the dehazed output.

Video Stitching:

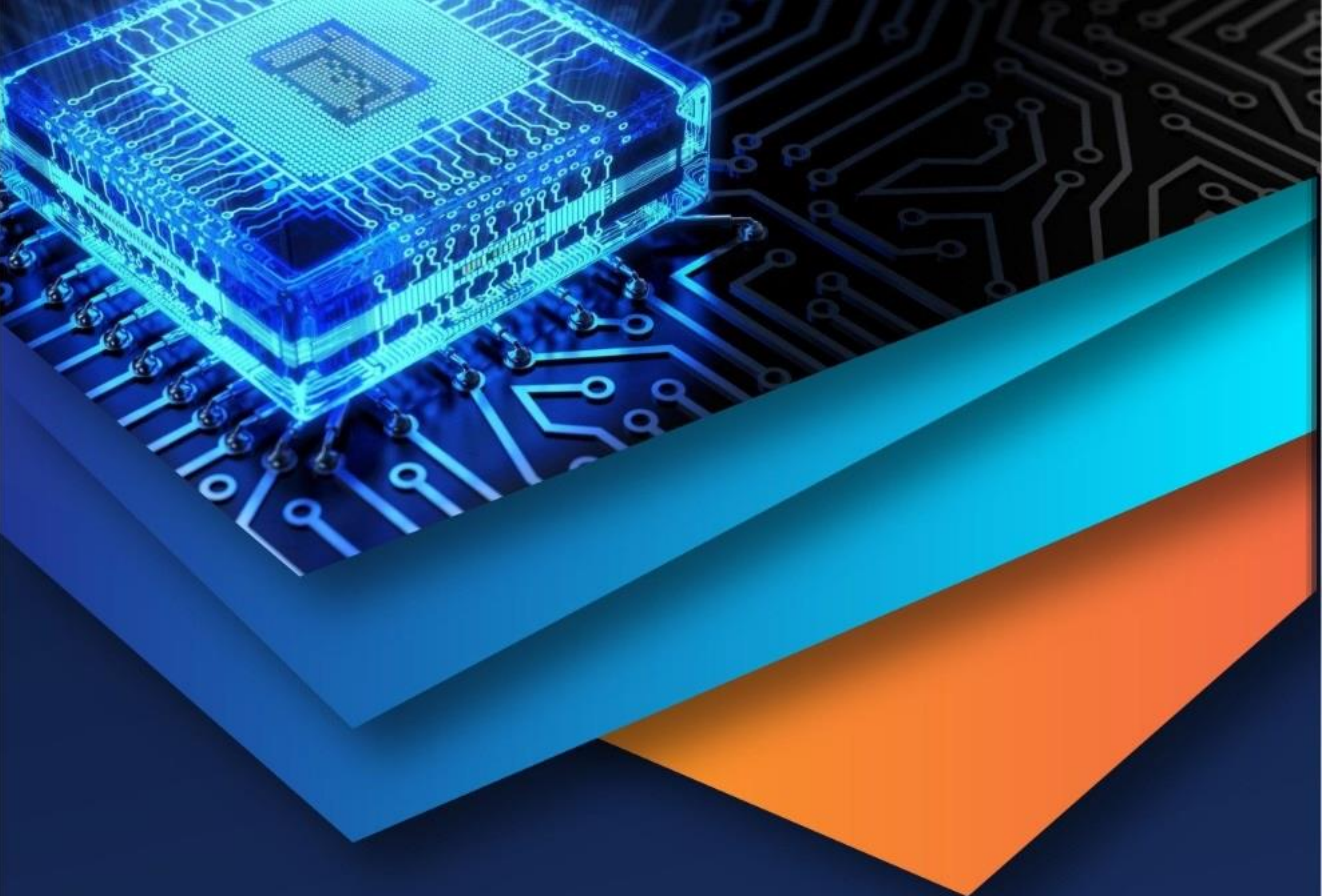
Frames are ordered and stitched together using OpenCV's video writing functionalities (Video Writer) to write each dehazed frame sequentially into a new video.
Using MoviePy Library, both the input video and output video are combined together, shown as the result.

V. CONCLUSION

The implementation of dehazing techniques for images of smoke and fire, coupled with YOLO (You Only Look Once) object detection, along with an Arduino-based window opening mechanism, presents a promising solution for improving visibility and safety in environments affected by smoke and fire. By leveraging advanced image processing algorithms and real-time object detection capabilities, this system can help mitigate the risks associated with fire incidents and aid in timely evacuation efforts.
The dehazing process effectively reduces the impact of smoke particles on image clarity, enhancing visibility for firefighters, rescue personnel, and surveillance systems. YOLO object detection further enables the identification and tracking of fire-related objects, facilitating situational awareness and decision-making during emergency scenarios.
The integration of Arduino-based window opening mechanisms adds a practical dimension to the system, allowing for automated ventilation in response to detected smoke or fire. By dynamically adjusting ventilation based on real-time environmental conditions, this feature enhances air quality, aids in smoke dispersion, and supports evacuation efforts by providing clearer escape routes.

REFERENCES

[1] Sergio Saponara on“Real-time fire/smoke detection based on CNN”(2020), Springer
[2] Chengtuo Jin on “Fire Detection Methods Based on Deep Learning: Datasets, Methods,and future directions”(2023) MDPI
[3] Ju Mingye on “Single image haze removal based on the improved atmospheric scattering model”(2020) ELSEVIER
[4] Shahid Mumtaz on “Energy-Efficient Deep CNN for Smoke Detection in Foggy IoT Environment”(2019) IEEE
[5] Chuansheng Wang , on “Color-Dense Illumination Adjustment Network for RemovingHaze And Smoke from Fire Scenario Images” (2022), MDPI
[6] Shuping Li “Image Dehazing Algorithm Based on Deep Learning Coupled Local and Global Features”(2022), MDPI
[7] Dengyin Zhang on “Real-time Image Haze Removal Method for Fire Scene Images”(2018), ICMMCT
[8] Zul Imran Azhari, Samsul Setumin on “Digital image enhancement by brightness and contrast manipulation using verilog hardware description language”(2023), ISSN
[9] Shuying Huang, Donglei Wu1 and Yong Yang on “Image Dehazing Based on RobustSparse Representation”(2018) , IEEE
[10] P. Tamil Mathi on “A SURVEY ON FOREST FIRE DETECTION”(2015), ISSN
[11] Jun Xu, Zi-Xuan Chen, Zi-Xuan Chen and Zhe-Ming Lu on “An Efficient Dehazing Algorithm Based on the Fusion of Transformer and Convolutional Neural Network”(2022), MDPI
[12] Donghui Zhao , Bo Mo , Xiang Zhu , Jie Zhao on “Dynamic Multi-Attention Dehazing Network with Adaptive Feature Fusion”(2022), MDPI
[13] Xin he , wanfeng ji, and jinpeng xie on “Unsupervised Haze Removal for Aerial Imagery Based on Asymmetric contrastive Cycle GAN”(2022), IEEE
[14] G. Harish Babu on “ABF de-hazing algorithm based on deep learning CNN for single I-Haze Detection” (2023), ELSEVIER



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